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CDEP-CGEG WP No. 53

How important are beliefs about gender differences in math ability? Transmission across generations and impacts on child outcomes

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December 2019

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Center on Global Economic Governance

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Abstract

We study the transmission of beliefs about gender differences in math ability from adults to children and how this affects girls' academic performance relative to boys. We exploit randomly assigned variation in the proportion of a child's middle school classmates whose parents believe boys are innately better than girls at learning math. An increase in exposure to peers whose parents report this belief increases a child's likelihood of believing it, with similar effects for boys and girls and greater effects from peers of the same gender. This exposure also affects children's perceived difficulty of math, aspirations, and math performance, generating gains for boys and losses for girls.

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1 Introduction

Societal beliefs about differential ability by gender contribute to individual belief formation (c.f., Jayachandran 2015; Nollenberger et al. 2016; Bian et al. 2017). This linkage can be harmful if it affects individual behavior and leads to discrepancies in subsequent outcomes. Prior work has shown that cultural norms about gender translate to differential effort, enthusiasm, and performance in school (Rodríguez-Planas and Nollenberger, 2018; Olivetti et al., Forthcoming), and contribute to the gender gap in labor market outcomes (Antecol, 2000, 2001; Rodríguez-Planas et al., 2018).

In this paper, we study how beliefs about differential ability of men and women transmit across generations and how this affects girls' academic performance relative to boys. Among the most common beliefs about differential gender ability is the belief that boys are innately better than girls at learning math (Tsui, 2007; Beilock et al., 2010; Jayachandran, 2015; OECD, 2015). We show that exposing a child to a greater number of peers whose parents hold this belief causes a child to be more likely to hold the belief themself. This effect is much greater when coming from peers of the same gender as the child. Exposure to this type of peer also affects how difficult the child perceives math to be, the child's educational aspirations, and the child's academic performance, generating gains for boys and losses for girls.

Our research design exploits the random assignment of children to classrooms in Chinese middle schools. We study the effects of random variation in the proportion of a child's peers whose parents believe that boys' innate math ability (B_m) is superior to girls' innate math ability (G_m).[1] In our data, roughly 40% of children's parents hold this belief, with substantial variation within schools, between classrooms. We estimate the impact of increases in exposure to peers whose parents believe $B_m > G_m$ on the following child outcomes: the child's likelihood of believing $B_m > G_m$ themself; the child's assessment of their own math ability; educational aspirations; and academic performance in math, Chinese, and English.

We find that exposure to a greater proportion of peers whose parents believe boys are better than girls at learning math increases the child's likelihood of holding the belief. We estimate that a one standard deviation (SD), or roughly 11 percentage point, increase in the proportion of peers whose parents believe $B_m > G_m$ increases the likelihood that a child holds the belief themself by 4.6 percentage points, from a baseline of 52 percent. These effects are monotonic over the distribution of the proportion of peers whose parents hold this belief. The magnitude of our estimates are similar for boys and for girls. Moving a child

[1] For shorthand, we refer to this as the proportion of peers whose parents believe $B_m > G_m$.

from the classroom in our sample with the lowest level of parents who hold the belief (no peers whose parents believe $B_m > G_m$) to the one with the highest level (where more than 83 percent of peers' parents hold the belief) would generate an increase of 34.8 percentage points in the likelihood of the child holding this belief themself.

We also find that children's beliefs are much more affected by peers of the same gender whose parents hold this belief.[2] We find that exposure to girl peers whose parents believe $B_m > G_m$ has roughly twice the impact on girls' beliefs as it does on boys' beliefs. We find similar, almost symmetric results showing greater effects of exposure to boy peers whose parents hold the belief on boys' beliefs, relative to its effect on girls' beliefs.

Next, we show that exposure to peers whose parents believe $B_m > G_m$ helps boys and harms girls in their performance in school. A one SD increase in the proportion of peers whose parents hold this belief worsens girls' standardized math test scores, relative to boys, by 0.06 SD. These effects, too, are monotonic over the distribution of the peer parent beliefs measure, with greater increases in the proportion of peers whose parents believe $B_m > G_m$ causing larger negative impacts on girls' relative math performance. The standardized effects on test scores are similar in magnitude to the 0.07 SD change in the gender gap in PISA test scores that is associated with a one standard deviation change in a country's gender equality index (Nollenberger et al., 2016; Rodríguez-Planas and Nollenberger, 2018). We also find larger test score effects from exposure to own-gendered peers whose parents hold the belief than from exposure to other-gendered peers.[3]

Exposure to these peers also affects girls' and boys' perception of their own math ability. We estimate that a one SD increase in exposure to peers whose parents hold this belief increases girls' likelihood of perceiving math to be difficult, relative to boys', by 1.9 percentage points. This constitutes a 25 percent increase in the gap between girls' and boys' perceived difficulty of math.

We see important heterogeneity within the negative effects on girls' beliefs, aspirations, and academic outcomes. First, these effects vary across different lengths of exposure to peers. We find that more time spent with peers whose parents believe $B_m > G_m$ increases the magnitude of the estimated effects, both on the likelihood a girl will herself hold that belief, and on the decline in her math test score relative to boys.

[2] This is a test for homophily: the tendency of individuals to associate with and learn from similar others (Currarini et al., 2009). In this setting, the most obvious dimension of similarity is by gender.

[3] We find negative but insignificant effects of this exposure on girls' academic performance, relative to boys, in two other subjects: Chinese and English tests.

Second, we see that the effects of exposure to peers whose parents believe $B_m > G_m$ are greater for girls whose own parents also hold this belief. Third, we find evidence that an important mitigating factor for these effects is the number of close friends that girls have in their randomly assigned classroom, corroborating recent work from Israel and Bangladesh (Hahn et al., Forthcoming; Lavy and Sand, Forthcoming).

Our main robustness exercises characterize the stability of parent beliefs. A weakness of our dataset is that data on parent beliefs are collected after children have been randomly assigned to classrooms. We evaluate the possibility that parents' beliefs may be affected by three aspects of the classroom their child is assigned to: the math ability of the other children in the classroom, the beliefs of the other parents in the classroom, and the gender of the teacher the child is randomly assigned to. Our tests find no evidence of any of these three channels, and their confidence intervals can reject even moderate effects. Our interpretation of these patterns is that adult beliefs are less malleable than child beliefs, because adults' beliefs have been formed by roughly three decades more of cumulative experience than children's beliefs have.

We also study the relative importance of two separate channels that contribute to our results. The first channel is from peer parent beliefs to peer child beliefs, and then on to the child herself. The second channel is the wide variety of other well-known sources of peer effects. These include the benefits that come from being assigned to a classroom with peers of higher ability (c.f., Zimmerman 2003; Feld and Zölitz 2017) or one with peers who have highly educated parents or parents with other beneficial traits (Fruehwirth and Gagete-Miranda, 2019; Olivetti et al., Forthcoming). We characterize the extent to which these two channels are distinct or whether, instead, our peer parent belief measure is merely another way to capture the broader, latent peer effect. We find that there is sufficient variation in peer parent beliefs to drive our results, independent of these three main sources of peer effects. We argue that this highlights the specific, independent role of the belief transmission channel in driving our main empirical results.

We make three main contributions. First, our findings advance recent work studying how beliefs form in children and the process of belief transmission from parent to child (e.g., González de San Román and de la Rica Goiricelaya, 2016; Rodríguez-Planas and Nollenberger, 2018; Dhar et al., 2018; Olivetti et al., Forthcoming). Second, they provide new evidence about the relationship between beliefs and differential academic performance by gender (e.g., Dee, 2007; Ellison and Swanson, 2010; Niederle and Vesterlund, 2010; Carlana, 2019). Third, our findings contribute evidence to the larger peer effects literature (e.g., Sacerdote et al., 2011; Lavy and Schlosser, 2011; Jain and Kapoor, 2015; Feld and Zölitz, 2017) on the role of an important, distinct channel for these effects - the impact of peers' parents and their beliefs on children's outcomes (e.g., Carrell and Hoekstra 2010; Bifulco et al. 2011; Fruehwirth and Gagete-Miranda 2019; Olivetti et al. Forthcoming).

The rest of the paper proceeds as follows. Section 2 describes the setting we study, our data, and our construction of the peer parent beliefs measure. Section 3 describes our empirical approach and Section 4 provides our main empirical results. Section 5 presents a series of robustness checks. Section 6 shows heterogeneity analyses and additional analysis of effects for girls. Section 7 concludes.

2 Background

In this section, we describe the setting which we study and the data we use. We finish by characterizing our peer parent beliefs measure, a key innovation of our paper, in greater detail.

2.1 Setting

Our analysis takes place in Chinese middle schools. This setting has three features which facilitate causal inference and the study of belief formation in children. The first feature is commonly but not universally held beliefs that boys are better than girls at learning math: in our sample, 41 percent of parents and, among children, 58 percent of boy and 47 percent of girl middle school students agree with the statement that "boys' natural ability in studying math is greater than that of girls."[4]

The second feature is the period of life we study. In China, the difficulty of the math curriculum in middle school increases substantially from that of primary school. This sudden increase in difficulty suggests that student priors about their own math ability and those of each gender are more likely to be updated at this juncture than in the upper years of primary school.[5]

The third feature is the random assignment of children to classrooms within schools. Students are usually allotted to middle schools by their local educational authority based on geographic proximity to schools. China's 2006 compulsory education law requires that, within middle schools, students be randomly assigned to classes. Several previous studies have exploited the random assignment of students to classrooms, and of students to teachers, created by this policy (e.g., He et al. 2017; Gong et al. 2018; Wang et al. 2018). As

[4] Despite this fact, the girls in our data outperform boys in math. The distribution of math test scores for the two groups is shown in Figure A.1.

[5] In Chinese primary school, the math curriculum usually covers arithmetic and basic conceptual reasoning. Middle school math content accelerates quickly, covering algebra, geometry, and more advanced logic and spatial reasoning.

we describe in Section 3, this random assignment prevents against the possibility that sorting by academic ability or parent preferences might confound our estimates.

2.2 Data

We use the first wave of the China Education Panel Survey (CEPS) for our empirical analysis. The CEPS is a nationally representative sample of Chinese middle school students, collecting a series of data from the students, their parents, their teachers, and their principals, planned to continue over several waves. The CEPS follows all students in two randomly selected seventh grade classes and two randomly selected ninth grade classes in each of 112 randomly selected schools.[6] These schools were selected using a nationally representative random sampling frame with selection probability proportional to size. The dataset comprises approximately 20,000 students, and the first wave was collected in the 2013-2014 academic year.[7]

The CEPS student data includes administrative data on the child's academic performance in mathematics, Chinese, and English, as well as the child's responses to a survey about their beliefs and aspirations. The parent data include a variety of demographic data as well as survey responses to a series of questions about the parent's beliefs. The teacher and administrator data include information on teacher characteristics and the method used to assign children to classes.

According to a law passed in 2006, Chinese middle schools are normally required to randomly assign children to classrooms. Under this system, children are assigned to a classroom at the start of seventh grade and will remain with the same peers in this randomly assigned classroom throughout middle school. In practice, some schools may deviate from this rule, for example, to sort children on ability.

We follow the same sample restriction employed in prior work using CEPS data: we analyze data from only those within-grade classroom pairs where principals and teachers report that random assignment was used to place children in classrooms (e.g., Hu, 2015, Gong et al., 2018, and Wang et al., 2018).[8] This generates a sample of 9,361 children in 215 classrooms spread across 86 schools, and this is the estimation

[6] Chinese middle schools typically span three grades: seven, eight, and nine. The median school in our dataset has six seventh grade classrooms and six ninth grade classrooms (mean: 7.3 and 6.9, respectively). There are not enough schools in our sample with only two classes per grade, i.e., where we would have all students in a grade, to study those as a separate subgroup.

[7] The second, latest available wave collects data only for a subset of children. We do not use it here because of its smaller sample size, and because it does not contain key data such as parent or child beliefs.

[8] Across China, various methods are used for assignment of children to classes, including random number generators, alphabetical assignment based on surname, and the system described in He et al. (2017) wherein an alternating sequence assigns students to classrooms sequentially based on entrance exam scores in a way that preserves mean test score balance and avoids stratification across classrooms. The randomness of assignment of children to classrooms in Chinese middle schools and its appropriateness for causal inference has been probed in several recent papers, many of which use this same dataset (Hu, 2015; Eble and Hu, 2019; He et al., 2017; Gong et al., 2018).

sample we use throughout our analysis in this paper. The excluded grade-by-school classroom pairs report either using methods other than random assignment to place children in classes, or re-sorting children to classrooms in the years after the initial random assignment. These are predominantly either ninth grade classrooms, where re-sorting often occurs due to administrative concerns about placing children in good high schools[9], or classrooms in rural areas, where enforcement of such rules is less strict overall.

We use four main outcome variables in our analysis. The first outcome variable is children's yes/no response to the question, "do you agree with the following statement: boys' natural ability in studying math is greater than that of girls?" The wording of this question is identical to that asked to parents; it refers to the innate math ability of each gender, not just the relative performance of boys and girls in the child's current school or class. For ease of exposition, we refer to this as the belief that boys are better than girls at learning math, or just $B_m > G_m$. The second outcome variable is the child's answer to the question "how difficult do you find your current math class?" The possible answers are "very hard," "somewhat hard," "not so hard," and "easy." We code this as a dummy variable equal to one if the response is "very hard" or "somewhat hard." The third outcome is the child's aspirations for their ultimate educational attainment, which we code as a dummy for aspiring to at least a university degree. The fourth and final main outcome is children's performance on their midterm math, English, and Chinese tests. All middle schools in our sample administer low-stakes midterm exams in the middle of the fall semester. All students within a grade, within a school, take the same midterm test in each subject, which is graded centrally at the school level.[10] The CEPS collects these grades directly from school administrative data and provides them in standardized form.[11] The CEPS also collects a variety of other data on students, parents, and teachers which we use for ancillary outcomes, summary statistics, and control variables. We describe these in further detail in the next section when we present our empirical strategy.

Table 1 presents summary statistics for students, by gender, for those students randomly assigned to

[9]In Table A.2, we show summary statistics of schools in our estimation sample separately by whether or not they contain grade 9 classrooms that maintain the randomization initiated in grade 7 (in other words, schools that do not re-sort students by ability in subsequent years). These two types of schools are similar on most observable characteristics (size, number of teachers, percent of teachers with a BA, whether they are private or public). The only significant difference we observe is that schools whose ninth grade classrooms do not maintain randomization are slightly higher-ranked than schools whose ninth grade classrooms do maintain randomization. This pattern is consistent with the fact that re-sorting of children by ability is regarded as a way for middle schools to improve the likelihood of sending top children to higher-ranked high schools, and middle school ranking partly reflects this placement record.

[10]In our sample, we have two classrooms in a given grade in each school, but the average school has seven classrooms per grade in total. This ensures that one classroom's gain in scores does not cause a 1-to-1 decrease in the performance of children in the other classroom.

[11]These scores are standardized for each subject, within a given grade within each school, to be mean 70 and SD 10

Table 1: Summary statistics

	(1) All children	(2) Girls only	(3) Boys only	(4) Differ-ence	(5) P-value
Age	13.23	13.17	13.28	-0.11	0.00
Holds agricultural hukou	0.49	0.48	0.51	-0.03	0.04
Number of siblings	0.71	0.76	0.66	0.10	0.00
Low income household	0.19	0.18	0.20	-0.02	0.01
Father's highest credential					
Middle school	0.41	0.41	0.42	-0.01	0.44
High school	0.26	0.25	0.26	-0.01	0.69
College	0.19	0.20	0.18	0.02	0.03
Mother's highest credential					
Middle school	0.38	0.39	0.37	0.02	0.01
High school	0.23	0.23	0.23	0.00	0.56
College	0.16	0.17	0.16	0.01	0.12
Ethnic minority	0.12	0.12	0.11	0.01	0.23
Math test score	70.1	70.9	69.4	1.50	0.00
English test score	70.1	73.0	67.4	5.60	0.00
Chinese test score	70.0	73.2	67.1	6.10	0.00
Number of observations	9,361	4,492	4,869	—	—

Note: this table presents summary statistics for observations in our estimation sample. The variables are all coded as 0 = No, 1 = Yes, except for age and number of siblings, which are self-explanatory, and test scores (mean = 70, SD = 10). "Holds agricultural hukou" means the residence permit of the household was given in a rural, agricultural (as opposed to non-agricultural, urban) locality. The fourth column presents the difference between the mean for girls and that for boys, and the fifth column presents the p-value of this difference.

classrooms (our estimation sample). The girls in our sample are slightly younger than the boys, and they are more likely to have wealthier, more educated parents. Girls also have more siblings, consistent with traditional norms and fertility responses to birth control policy in China which permits further parity, in some cases, if the first child is a girl (Qian, 2008). Finally, in all subjects, girls perform better than boys on average.[12] In Figure A.1, we show the distribution of math test scores by gender. The distribution for girls first-order stochastically dominates that for boys (p-value < 0.001), with the largest difference in the left tail of the distribution.

2.3 Our measure of peer parents' beliefs

In this subsection, we describe how we construct our measure of the proportion of peers whose parents believe boys are innately better than girls at learning math. We also describe the properties of this measure.

We wish to measure a latent variable: each parent's beliefs about the innate ability of boys and girls in math. To do so, we use a data point the CEPS collects from the interviewed parent of each child to proxy for this. The CEPS asks the parent whether or not they agree with the statement "boys' natural ability in studying math is greater than that of girls." As with children's beliefs, we refer to this as the parent believing $B_m > G_m$. Approximately 41 percent of parents agree with the statement.[13]

We use this question to generate a child-level variable summarizing the beliefs of the parents of the child's peers in their randomly assigned classroom. Specifically, we create a leave-one-out measure which captures, for each child, the proportion of peers in their classroom whose parents report believing $B_m > G_m$, a variable which could potentially range from 0 to 1. In our data, the actual values of the variable range from 0 to 0.833, with a mean of 0.410 and a standard deviation of 0.112. At three significant figures, the mean of this variable is the same for girls and boys. Once standardized, the variable ranges from -3.597 SD to 3.739 SD. The distribution of parent beliefs at the classroom level mirrors the distribution for children. From here onward, we refer to this variable as our "measure of peer parent beliefs."

[12] In the 2009 PISA results for China, boys significantly outperformed girls in math. In the 2015 PISA results, this difference was no longer significant. These data, however, apply only to a select group of children from urban areas: Shanghai (2009) or Beijing, Shanghai, Jiangsu, and Guangdong (2015). Our data come from a nationally representative sample of middle schools across China and include both rural and urban areas.

[13] This belief is common despite the fact that, in China, girls generally outperform boys in math at this level of schooling (Gong et al., 2018). We argue that this pattern is at least partly the result of the fact that parent beliefs were most likely formed when the parent was a child, since beliefs are generally more malleable at younger ages. The parents of the children in our sample were themselves children in the 1970's and 1980's. At that time, son preference in China was stronger (Chen and Ge, 2018), and the phenomenon of boys outperforming girls was also far more common, meaning that the belief was more "representative," as in Bordalo et al. (2016).

Table 2: Characteristics of children, by whether parents report $B_m > G_m$

	(1) Full sample	(2) Believes $B_m > G_m$	(3) Does not believe	(4) Differ-ence	(5) P-value
Ethnic minority	0.12	0.12	0.11	0.01	0.12
Holds agricultural hukou	0.49	0.48	0.50	-0.02	0.12
Number of siblings	0.71	0.66	0.69	-0.03	0.08
Low income household	0.19	0.17	0.19	-0.02	0.02
Mother's years of schooling	9.88	10.04	9.95	0.09	0.27
Father's years of schooling	10.61	10.76	10.66	0.10	0.20
Child is female	0.48	0.45	0.51	-0.06	0.00
Parent's age	41.97	41.26	41.04	0.22	0.04
Number of observations	9,361	3,675	5,294	—	—

Note: this table gives summary statistics for children in our estimation sample, separately for those whose parents do (Column 2) and do not (Column 3) claim to believe that boys are better than girls at learning math. The variables are all coded as 0 = No, 1 = Yes, except for age, number of siblings, and parental years of schooling.

In Table 2, we summarize the characteristics of parents who do and do not believe $B_m > G_m$. We see differences for some characteristics (household income, number of siblings, parent's age, gender of the child), but these differences are small in magnitude. Our interpretation of the patterns in this table is that, overall, these two groups of parents are similar on most observable characteristics associated with the other traditional drivers of peer effects. This suggests that much of the variation in peer parent beliefs we measure is idiosyncratic to previously studied sources of peer effects.

There are two sources of variation in the classroom average proportion of parents who believe $B_m > G_m$: one, differences between schools, and two, differences between classes, within schools (the latter being our level of comparison). We next characterize the contribution of each source to the overall variation we see in our peer parent beliefs measure. Were our variation to come predominantly from between-school differences, then our comparison between classes, within a grade within each school, could precisely estimate the impact of small changes in peer parent beliefs. This comparison, however, would have little to say about larger changes, as they would necessitate out-of-sample predictions.

We find substantial variation in parent beliefs between classrooms, within a grade, within a given school. In Figure 1, we show two plots describing the variation between classrooms in the proportion of parents who believe $B_m > G_m$. Panel A shows, for each classroom, the proportion of parents who agree with the statement that boys are better than girls in learning math. This shows a roughly symmetric distribution around 41%, the mean, with a range from 7% to almost 80%. Panel B shows how our measure of parent beliefs varies within each of the 86 within-school, within-grade pairs of classrooms in our data. We plot each pair as a point, with the standardized class-average parent beliefs for class 1 shown on the x-axis, and that for class 2 on the y-axis. We see large differences in parent beliefs between classrooms in these pairs. A simple decomposition of variance finds that between-school variation explains less than a third of the overall variation in classroom-level parent beliefs.[14]

3 Empirical strategy

This section explains our approach to estimation, tests our main identifying assumption (random assignment of children to classrooms), and discusses a few key issues related to the interpretation of our main coefficient estimates.

3.1 Estimation

In our empirical analysis, we focus on estimating two key relationships: one, the effect of exposure to peers whose parents believe $B_m > G_m$ on a child's outcomes; and two, how this varies with the child's gender. Our identification strategy is to exploit random variation between classrooms in a given grade, within a given school, in the proportion of peers whose parents hold this belief. Our main estimating equation is as follows:

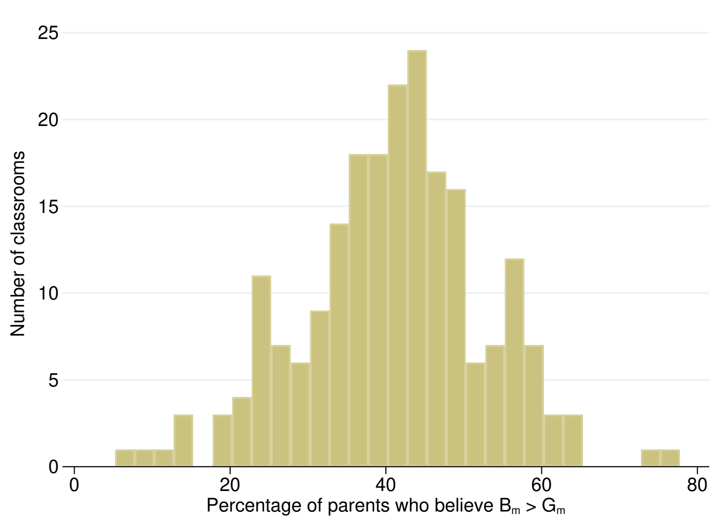
$$\begin{aligned} Y_{icgs} = \beta_0 + \beta_1 PPB_{icgs} + \beta_2 PPB_{icgs} * F_{icgs} + \beta_3 OPB_{icgs} + \beta_4 OPB_{icgs} * F_{icgs} \\ + \beta_5 F_{icgs} + \beta_6 SC_{icgs} + \beta_7 TC_{cgs} + \eta_{gs} + \varepsilon_{icgs} \end{aligned} \tag{1}$$

In this equation, Y_{icgs} refers to the outcome of interest for child i in class c in grade g in school s.[15] PPB_{icgs} is the proportion of child i's peers in their classroom whose parents believe $B_m > G_m$, standardized

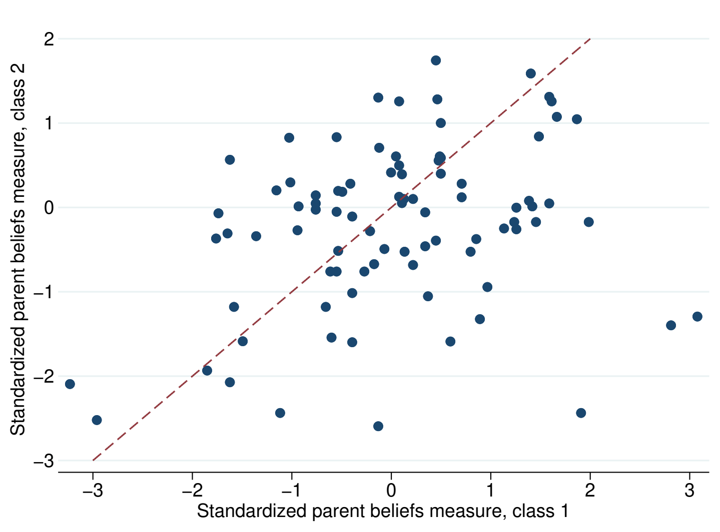
[14] A separate way to capture the differences between classrooms, within a grade, within each school, is to calculate the absolute value of the difference in the (standardized) parent beliefs measure between classroom 1 and classroom 2. We calculate this value for every grade-by-school pair of classrooms; its value varies between 0.1 and 4.35 SD, with a mean of 1 SD. We show the distribution of these values in Figure A.2.

[15] This setup follows convention among studies using plausibly random assignment to classrooms as a source of identification, e.g. Ammermueller and Pischke (2009) and Feld and Zölitz (2017).

Figure 1: Dispersion of parent beliefs across classrooms



Panel A: Dispersion of parent beliefs across classrooms, raw data



Panel B: Standardized classroom-level parent beliefs by within-school, within-grade classroom pair

Note: Panel A of this figure shows the distribution of the classroom average of the (non-standardized) parent beliefs measure across all classrooms in our estimation sample. Panel B shows the average (standardized) parent belief measure in classroom 1 and classroom 2 for each of our within-grade, within-school classroom pairs. Variation between classrooms in a pair is the dimension of variation we use in our analysis. For comparison, we overlay the 45 degree line on this figure to represent the special case with no such variation. Each point's distance from the line shows the within-school, within-grade, between-classroom difference in the proportion of parents who believe $B_m > G_m$ for that pair of classrooms.

to be mean 0, SD 1. F_{icgs} is an indicator for the child being female. OPB_{icgs} is an indicator for whether the child's own parent believes $B_m > G_m$. SC_{icgs} is a vector of characteristics specific to the student, including: rural vs. urban household residency (hukou) status, mother's years of education, father's years of education, household income (a 0/1 variable for being classified as "poor" by the school), these three interacted with the child's gender, the child's ethnicity, the number of siblings the child has, and the child's perceived ability, proxied by their perceived difficulty of mathematics in the sixth grade. TC_{cgs} is a vector of teacher characteristics including: teacher gender; teacher gender interacted with child gender; years of experience; type of degree; and receipt of various teaching awards. η_{gs} is a grade-by-school fixed effect[16], and ε_{icgs} is a standard error, clustered at the grade-by-school level.

We include the child's own parent's beliefs for three reasons. One, prior empirical work estimating peer parent to child effects usually includes the child's own parents' characteristic of interest in addition to those of peers' parents (Bifulco et al., 2011; Fruehwirth and Gagete-Miranda, 2019; Olivetti et al., Forthcoming). Two, the own-parent-to-child correlation is an object of separate interest – for example, it is the main focus of Dhar et al. (2018) – and it allows us to benchmark the relative importance of peer parents' and own parent's beliefs. Finally, we include own parent beliefs because later in the paper we study whether there is heterogeneity in the effects of exposure to peers whose parents believe $B_m > G_m$ by whether the child's own parent holds the belief. In the appendix we present a series of parallel tables for our main analyses which show our results estimated while excluding the own parent's belief variable from the list of controls. Our findings are robust to choice of specification.

Our main coefficients of interest are β_1 and β_2. The coefficient β_1 captures the impact of a one SD - or 11.2 percentage point - increase in the proportion of peers whose parents believe $B_m > G_m$ on boys' outcomes. The coefficient β_2 captures the impact of a one SD increase in this measure of peer parent beliefs on girls' outcomes, relative to boys; equivalently, this is the impact of peer parent beliefs on the "gender gap" (c.f., Muralidharan and Sheth, 2016). The overall effect of exposure to peers whose parents believe $B_m > G_m$ on girls' outcomes is captured by $\beta_1 + \beta_2$.

[16] We do not use classroom fixed effects because we wish to exploit the variation in peer parent beliefs between classrooms within a grade within a school.

3.2 Assessing random assignment

In this section, we evaluate our claim that children are randomly assigned to their classrooms. First, note that we follow the sample restriction of several previous papers which have used these data. These papers show that using this sample restriction yields a dataset of children who are randomly assigned to classrooms within a school, as evidenced by results from standard tests of randomization/balance (e.g., Table 1 in Hu, 2015; Table 2 in Gong et al., 2018; and Table 3 in Wang et al., 2018).

We further probe the claim of random assignment of children to classrooms by regressing our peer parent beliefs measure on the child-level characteristics in SC_{icgs}, all of which are predetermined relative to classroom assignment. This approach follows Antecol et al. (2015), Bruhn and McKenzie (2009), and Hansen and Bowers (2008). We present our results in Table 3: in Column 1, we show the results for regressing peer parent beliefs on the vector of predetermined characteristics without any fixed effects; in Column 2, we add controls for the grade-by-school fixed effects used in our main estimating equation. Our results in Column 2 fail to reject the null that the regressors do not significantly predict variation in peer parent beliefs within schools, within grades, between classrooms. We find similar results if we conduct the test separately by the grade a student is in, reported in Table A.1.

The random assignment of children to classes prevents our estimates of β_1 and β_2 from being confounded by potential non-random sorting of children to classrooms, either by ability or parent preference. Were such sorting to exist, our estimates of the effect of exposure to more peers whose parents believe $B_m > G_m$ would also comprise the other effects of such sorting. For example, since girls outperform boys in math in our sample (see Figure A.1), placing more able students together would lead to more girls in higher performing classrooms. This would lead to two differences: one, more girl-to-girl (boy-to-boy) exposure in high-performing (low-performing) classrooms; two, in high performing classrooms, greater salutary effects of having more girl peers (Hu, 2015). Random assignment also prevents two other potential confounders: one, that schools reallocate teacher and classroom resources towards (or away from) higher-ability classrooms; two, that parents with certain characteristics request their children to be among the children of similar parents.

Table 3: Test for randomization / balance

	(1)	(2)
Age	0.124***	-0.010
	(0.050)	(0.007)
Holds agricultural hukou	-0.120	0.014
	(0.074)	(0.019)
Number of siblings	-0.081**	-0.006
	(0.041)	(0.008)
Household is poor	-0.064	0.044**
	(0.071)	(0.020)
Female	0.024	0.015
	(0.029)	(0.011)
Mother's highest credential		
Middle school	-0.060	0.013
	(0.070)	(0.016)
High/technical school	0.071	0.026
	(0.080)	(0.021)
College or above	0.108	0.023
	(0.082)	(0.025)
Father's highest credential		
Middle school	-0.023	0.004
	(0.046)	(0.017)
High/technical school	0.067	0.007
	(0.068)	(0.029)
College or above	0.060	0.018
	(0.081)	(0.032)
Ethnic minority	0.148	-0.009
	(0.250)	(0.023)
Number of observations	8,964	8,964
Grade-by-school fixed effects		X
Joint test F-statistic	2.19	1.13
[p-value]	[0.02]	[0.35]

Note: this table presents a balancing test, as in Antecol et al. (2015), which tests for our set of predetermined characteristics' joint ability to predict the peer parent beliefs measure by regressing the peer parent belief measure on them, using our estimating equation, and calculating the joint F-statistic and its p-value. Grade-by-school fixed effects are added to the estimating equation to generate the estimates in Column 2. Variables are all coded as 0 = No, 1 = Yes, except for age and number of siblings, which are self-explanatory. The dependent variable, peer parent beliefs, is standardized (mean = 0, SD = 1).

4 Main empirical results

In this section, we present our main estimates of the effect of being exposed to peers whose parents believe that boys are better than girls at learning math. The dependent variables we study in this section are children's likelihood of holding this belief themselves, assessment of their own math ability, educational aspirations, and performance on standardized math examinations. Sections 5 and 6 present robustness, estimates for other outcomes such as Chinese and English test scores, and heterogeneity.

4.1 Beliefs

We estimate the relationship between exposure to peers whose parents believe $B_m > G_m$ and three variables capturing children's beliefs: whether or not the child themself believes $B_m > G_m$, the child's perceived ability in math, and the child's educational aspirations.

We present these results in Table 4. This table follows the convention that we will use for most of our main result tables. First, we present the estimate for exposure to peers whose parents believe $B_m > G_m$ (β_1), labeled as "peer parent beliefs" or "PPB." We also present its interaction with whether the child is female (β_2), labeled in the tables as "PPB x female." In addition, we present the coefficients for own parent beliefs (β_3, labeled as "own parent beliefs" or "OPB" in the tables) and its interaction with the female dummy (β_4, "OPB x female"). Finally, we present the coefficient estimate for the child being female (β_5).[17]

In the first column, we present our estimates of how exposure to peers whose parents believe $B_m > G_m$ affects children's beliefs. We estimate that a one standard deviation increase in the peer parent belief measure is associated with a 4.6 percentage point (8.7%) increase in the likelihood that a child will believe $B_m > G_m$ herself (β_1 = PPB). The estimate is similar for girls and boys: β_2 (PPB x female) is not statistically distinguishable from zero. In Figure 2, we plot this relationship non-parametrically, separately for boys and for girls. We show a kernel-weighted local polynomial regression of child beliefs on the peer parent beliefs measure. The figure shows that the relationship between exposure to peers whose parents believe $B_m > G_m$ and children's own likelihood of reporting the belief is monotonic over the support of our peer parent beliefs measure. Going from a classroom in which roughly 25 percent of peers' parents believe $B_m > G_m$ to one where 75 percent of peers' parents hold this belief generates a 20.6 percentage point (39%) change in the

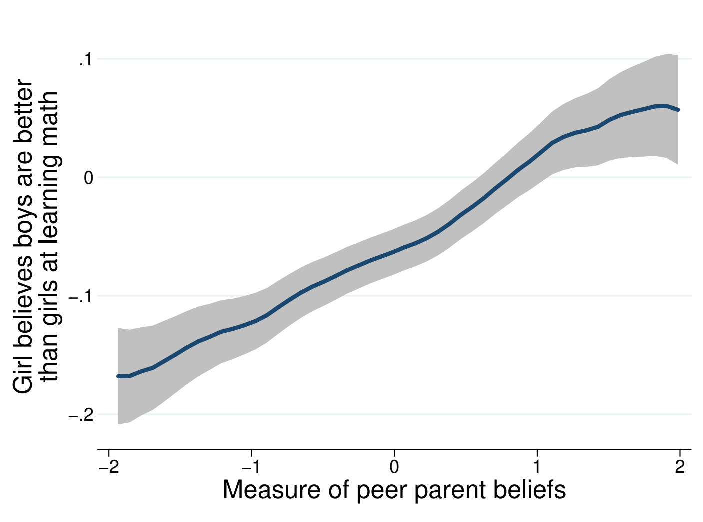
[17]Unless otherwise noted, variation in the number of observations comes from variation in the number of missing values across dependent variables. Our results are robust to restricting the sample to only those observations who have non-missing values for all dependent variables.

Table 4: Effects on beliefs and aspirations

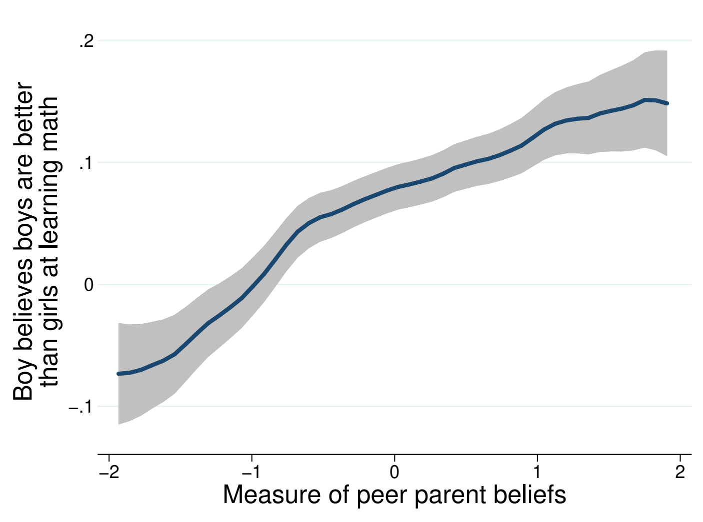
	(1) Believes boys are better than girls at learning math	(2) Perceives current math class to be difficult	(3) Aspires to complete at least a BA
Peer parent beliefs (PPB)	0.046***	-0.011	0.002
	(0.012)	(0.016)	(0.017)
PPB x female	0.002	0.019**	0.008
	(0.014)	(0.009)	(0.010)
Own parent beliefs (OPB)	0.286***	-0.065***	0.018
	(0.016)	(0.016)	(0.014)
OPB x female	0.030	0.152***	-0.013
	(0.020)	(0.023)	(0.020)
Female	-0.129***	-0.013	0.101***
	(0.032)	(0.028)	(0.023)
Mean in sample	0.526	0.570	0.658
Observations	8,057	8,212	8,173

Note: this table shows results from estimating equation 1 using the dependent variable named in the column heading and described in the text. Variation in the number of observations across columns stems from differences in missing values for the dependent variables. The dependent variables are given below the column numbers and are coded as 0 = No, 1 = Yes. In Table A.3, we show the analog to these results generated without own parent beliefs on the right hand side.

Figure 2: Non-parametric relationships between exposure to peers whose parents believe $B_m > G_m$ and child beliefs, by gender



Panel A: Girls



Panel B: Boys

Note: this figure shows a kernel-weighted local polynomial regression of a child's likelihood of reporting that boys are better than girls at learning math (0 = No, 1 = Yes) on the proportion of peers whose parents hold this belief, after removing grade-by-school fixed effects from the dependent (y-axis) variable. Panel A presents this relationship for girls in our sample, and Panel B presents it for boys. Note that a one unit increase in the peer parent beliefs measure (the x-axis variable) is equivalent to an 11 percentage point increase in the proportion of peers whose parents believe $B_m > G_m$.

likelihood that a child will also hold that belief.[18]

Referring back to the results in Column 1 of Table 4, we note that the coefficient on own parent beliefs is large in magnitude, statistically significant, and has the same sign as the coefficient for peer parent beliefs. Children whose parents believe boys are better than girls at learning math are 29 percentage points (56%) more likely to also hold that belief. This relationship also holds similarly for boys and for girls.[19] These coefficients are comparable in magnitude to going from the classroom with the fewest possible peers whose parents who hold the belief (none) to the classroom with the largest proportion of peers (83.3%) whose parents believe $B_m > G_m$.[20] Finally, the coefficient on the female gender dummy shows that girls are less likely than boys to espouse the belief that boys are better than girls at learning math.

In the second column, we show results for perceived difficulty of math. Here the signs of the estimates diverge for boys and girls, and we estimate that a one SD increase in exposure to peers whose parents believe $B_m > G_m$ increases girls' likelihood of perceiving math to be difficult, relative to boys', by 1.9 percentage points, or an increase of 25 percent in the 7.7 percentage point average difference between girls and boys seen in the raw data. The own parent beliefs coefficients again share signs with the peer parent beliefs coefficients. If a girl's own parent believes $B_m > G_m$, she is 15.2 percentage points more likely to perceive math to be difficult, relative to boys whose parents also hold this belief. In the final column, we find no evidence that exposure to peers whose parents believe $B_m > G_m$ affects aspirations to complete at least a BA. In Section 6, however, we show significant, heterogeneous effects of exposure to these peers on girls' educational aspirations.

We next study how these patterns vary with exposure to peers of different genders. For each child, we compute two class-specific measures of the proportion of peers whose parents believe $B_m > G_m$, one for girl peers' parents and one for boy peers' parents. This is a test for homophily, the idea that children who share an identity (e.g., gender) are more likely to interact and/or serve as credible sources of information, and thus are more "influential" in the transmission of beliefs than are children outside the identity group (Currarini et al., 2009). We present these results in Table 5. Columns 1 and 3 show that own-gendered peers have a greater impact on a child's likelihood of holding the belief than do other-gendered peers. The

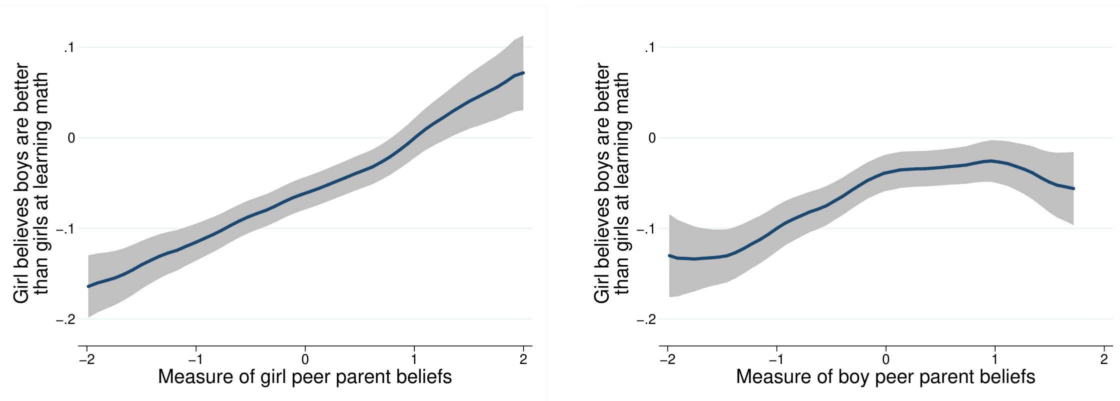
[18] Going from 25% of peers whose parents believe $B_m > G_m$ to 75% comprises a 4.48 SD change in peer parent beliefs.

[19] This estimate is substantially larger than the 11 percentage point increase for Indian secondary school children whose parents hold this belief found in Dhar et al. (2018).

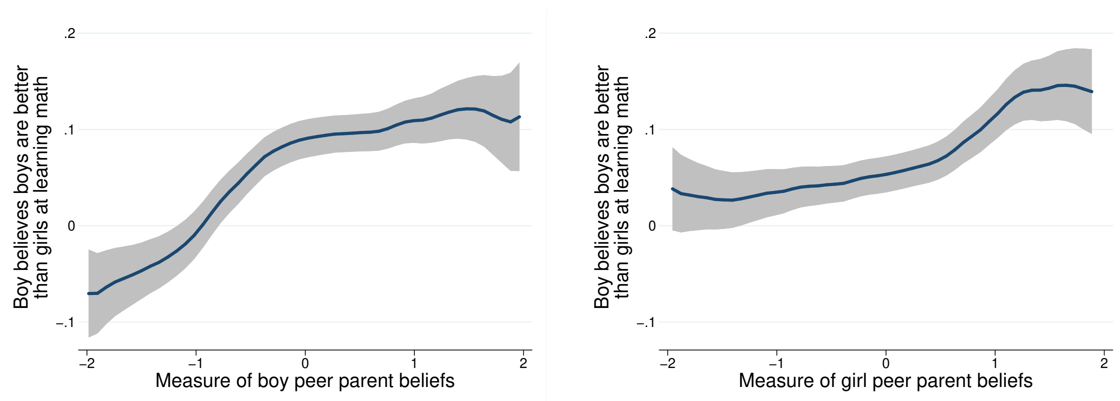
[20] Throughout our results, the ratio of the magnitude of the estimate for a one SD increase in peer parent beliefs measure and that for turning on the own parent beliefs measure is consistently between 1:4 and 1:8. This regularity may provide some suggestive information about the relative importance of peer parent and own parent influence on child beliefs and outcomes at this stage of life.

Figure 3: Homophily in the effects of exposure to peers whose parents believe $B_m > G_m$ on child beliefs

Own-gendered peers *Other-gendered peers*



Panel A: Girls



Panel B: Boys

Note: this figure shows a kernel-weighted local polynomial regression of a child's likelihood of reporting that boys are better than girls at learning math (0 = No, 1 = Yes) on the proportion of peers whose parents hold that belief, after removing grade-by-school fixed effects from the dependent (y-axis) variable, as in Figure 2. Here the four plots are divided by child gender (girls in the first panel, boys in the second) and the gender of the peers used to create the peer parent beliefs measure (parents of own-gendered peers in the left column, and those of other-gendered peers in the right). As in Figure 2, a one unit increase in the peer parent beliefs measure (the x-axis variable) is equivalent to an 11 percentage point increase in the proportion of own- or other-gendered peers whose parents believe $B_m > G_m$.

Table 5: Evidence of homophily among peers in belief transmission

	Girl peers' parents' beliefs		*Boy peers' parents' beliefs*	
	(1)	(2)	(3)	(4)
	Believes boys are better than girls at learning math	Perceives math to be difficult	Believes boys are better than girls at learning math	Perceives math to be difficult
Gender-specific peer parent beliefs (PPB)	0.017	-0.005	0.043***	-0.006
	(0.014)	(0.015)	(0.011)	(0.012)
Gender-specific PPB x female	0.025*	0.020*	-0.015	0.005
	(0.014)	(0.011)	(0.014)	(0.008)
Own parent's beliefs (OPB)	0.282***	-0.066***	0.285***	-0.067***
	(0.016)	(0.016)	(0.016)	(0.016)
OPB x female	0.031	0.154***	0.027	0.156***
	(0.021)	(0.023)	(0.020)	(0.024)
Female	-0.131***	-0.013	-0.126***	-0.013
	(0.032)	(0.028)	(0.032)	(0.028)
Mean in sample	0.526	0.570	0.526	0.570
Observations	8,056	8,211	8,057	8,212

Note: this table shows results for estimating the effects of exposure to girl and boy peers whose parents believe $B_m > G_m$ separately, as indicated in the two table headings. The dependent variables are given below the column numbers and are coded 0 = No, 1 = Yes. In Table A.4, we show the analog to these results generated without own parent beliefs on the right hand side.

boy peer-to-boy estimate (β_1, or the PPB estimate in Column 3) is 0.043, and the girl peer-to-girl estimate ($\beta_1 + \beta_2$, or the PPB + PPB x female estimate in Column 1) is 0.042. The magnitude of these estimates from exposure to other-gendered peers are substantially smaller: for girl peers to boys – the PPB estimate in Column 1 – this is 0.017. For boy peers to girls – the PPB + PPB x female estimate in Column 3 – this is 0.028. The estimates in Columns 2 and 4 are less precise than their counterparts in Table 4, but we show in Table A.4 that taking out the control for own parent beliefs generates homophily estimates for perceived difficulty of math whose magnitudes are similar to those shown here and which are statistically significant at the 1% level.

In Figure 3, we show the peer gender-specific analogue to the non-parametric relationship between peer parent beliefs and child beliefs shown in Figure 2. These show a monotonic mapping from exposure to peers whose parents believe $B_m > G_m$ and the child's likelihood of holding the belief, with visibly steeper gradients from exposure to own-gendered peers than from exposure to other-gendered peers. As a whole,

Table 6: Effects on performance in math

	(1) All peers' parents' beliefs	(2) Boy peers' parents' beliefs	(3) Girl peers' parents' beliefs
Peer parent beliefs (PPB)	0.039 (0.039)	0.081** (0.037)	-0.054 (0.037)
PPB x female	-0.057** (0.025)	-0.045* (0.023)	-0.023 (0.025)
Own parent beliefs (OPB)	0.169*** (0.027)	0.178*** (0.027)	0.172*** (0.026)
OPB x female	-0.291*** (0.041)	-0.305*** (0.042)	-0.308*** (0.043)
Female	0.355*** (0.056)	0.358*** (0.056)	0.357*** (0.055)
Observations		8,028	

Note: in all regressions, the dependent variable is the student's test score on a midterm math test. The math test score variable is continuous and standardized to be mean 0, SD 1. The observations in this sample reflect all students for whom we have a math test score. Different columns pertain to different measures of peer parent beliefs as labeled in the column headings. In Table A.5, we show the analog to these results generated without own parent beliefs on the right hand side.

we interpret the results from Table 5, Table A.4, and Figure 3 as evidence that a child's beliefs are more affected by exposure to peers of the same gender whose parents believe $B_m > G_m$ than by exposure to peers of the opposite gender whose parents hold the belief. In other words, the effects of exposure to peers whose parents believe that boys are better than girls at learning math are characterized by homophily.

4.2 Performance on math examinations

Next, we study the effect of exposure to peers whose parents believe that boys are better than girls at learning math on children's performance in math. In Table 6, we present results from estimating equation 1 with these math test scores as the dependent variable. Column 1 shows results for exposure to all peers whose parents believe $B_m > G_m$. Columns 2 and 3 show results for exposure to boy and girl peers whose parents hold the belief, respectively, akin to the results shown in Table 5.

As shown in Column 1, a one SD increase in exposure to peers whose parents hold the belief worsens girls' performance, relative to boys', by 0.057 SD. We plot this relationship non-parametrically in Figure 4, separately for boys and for girls. This figure shows a kernel-weighted local polynomial regression of the math test scores of boys and, separately, of girls, on our peer parent beliefs measure. These plots show a similar monotonic relationship between exposure to peers whose parents hold the belief and children's performance in mathematics, with gains for boys and losses for girls.

The coefficients for own parent beliefs and own parent beliefs x female are again large and in the same direction as the peer parent beliefs coefficients. The scores of boys whose parents believe that boys are better than girls at learning math are 0.17 SD higher than for boys whose parents do not believe this. Girls who have a parent who holds this belief have 0.29 SD lower math test scores than boys who do.

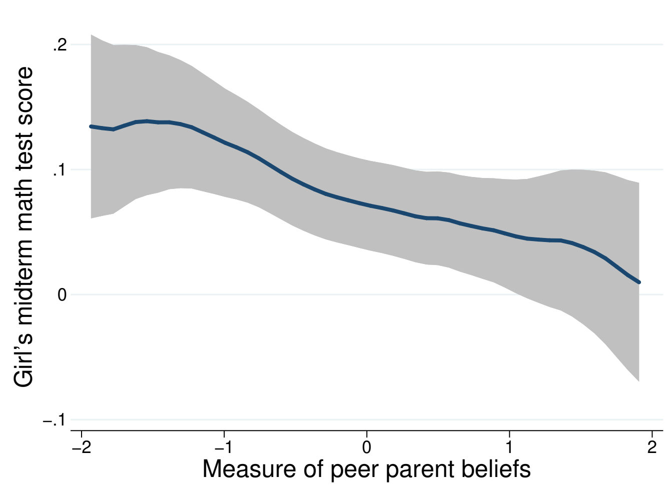
In Columns 2 and 3 of Table 6, we test for homophily, i.e., greater effects of exposure to own-gendered peers whose parents believe $B_m > G_m$ on math test scores, relative to the effects of exposure to other-gendered peers. We see evidence of this pattern, in line with what we find in Table 5. Our estimated effects of exposure to boy peers whose parents hold this belief on boys' test scores are positive and significant. The negative, marginally significant estimate of β_2 (the effect on girls' scores, relative to boys) suggests these effects are different by gender. For exposure to girl peers whose parents hold this belief, we see negative estimates of both coefficients. The total effect of exposure to girl peer parents who believe $B_m > G_m$ on girls is $\beta_1 + \beta_2 = -0.077$, roughly symmetric to the effect of exposure to boy peer parents who hold this belief on boys, $\beta_1 = 0.081$. While neither coefficient in the girl peer parent beliefs estimates is significant at traditional levels by itself, an F-test rejects the null that the total effect for girls, $\beta_1 + \beta_2$, is zero (F-stat 5.86, p-value 0.017).[21] In Figure 5, we show the same kernel-weighted local polynomial regression of child test scores on exposure to peers whose parents believe $B_m > G_m$, separately for own-gendered and other-gendered peers, as in Figure 3. The differences in the magnitude of the gradient between own-gendered and other-gendered peers in these figures also show evidence of homophily.

5 Robustness and interpretation of results

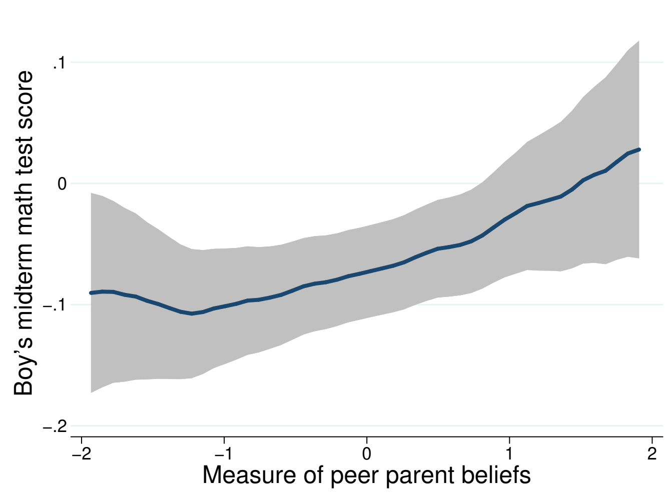
In this section, we show two sets of results. The first, in Section 5.1, shows that our findings are robust to the main threat to identification, that parent beliefs are affected by the random assignment of their children to classrooms. This can flow through either the ability of the other children in their child's randomly assigned

[21] Analogue results estimated without the own parent beliefs coefficients, shown in Table A.5, give similar results suggesting homophily, with more precise effect estimates.

Figure 4: Non-parametric relationships between exposure to peers whose parents believe $B_m > G_m$ and test scores, by gender



Panel A: Girls

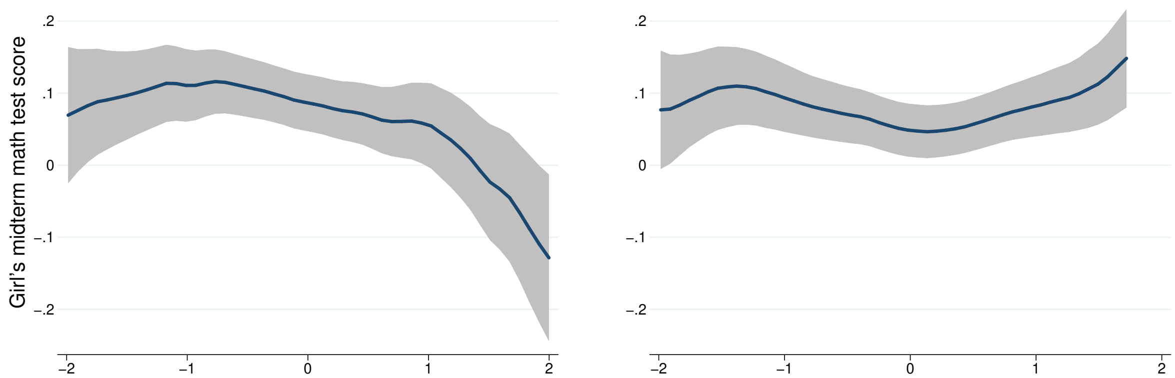


Panel B: Boys

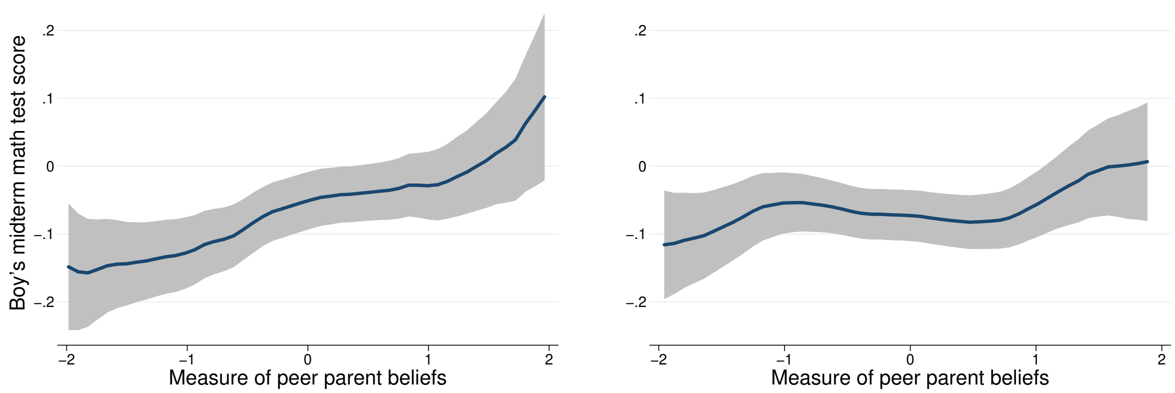
Note: this figure shows the kernel-weighted local polynomial regression of the child's performance on their midterm math test (in SD units) on the individual-level measure of exposure to peers whose parents believe $B_m > G_m$, again with grade-by-school fixed effects removed from the y-axis variable. Panel A presents this relationship for girls in our sample, and Panel B presents it for boys. A one unit increase in the peer parent beliefs measure (the x-axis variable) corresponds to an 11 percentage point increase in the proportion of peers whose parents hold the belief.

Figure 5: Homophily in the effects of exposure to peers whose parents believe $B_m > G_m$ on math test performance

Own-gendered peers *Other-gendered peers*



Panel A: Girls



Panel B: Boys

Note: this figure shows a kernel-weighted local polynomial regression of children's performance on midterm math examinations (in SD units) on exposure to peers whose parents believe $B_m > G_m$, again with grade-by-school fixed effects removed from the y-axis variable. Here the four plots are divided by child gender (girls in the first panel, boys in the second) and the gender of the peers used to create the peer parent beliefs measure (parents of own-gendered peers in the left column, and those of other-gendered peers in the right). A one unit increase in the peer parent beliefs measure (the x-axis variable) corresponds to an 11 percentage point increase in the proportion of peers whose parents hold the belief.

classroom, the beliefs of these children's parents, or the gender of the teacher. The second set of results, in Section 5.2, shows that the main mechanism behind our findings is the transmission of beliefs from peers' parents, and not the many other sources of peer effects. At the end of the section, we describe how we interpret our estimates of β_1 and β_2 in light of this section's findings.

5.1 Robustness

In this subsection, we address the potential for parent beliefs to be affected by the characteristics of the classroom their child was assigned to. A weakness of our data is that the parent survey was administered after the child was randomly assigned to a classroom. This means that, potentially, our estimates of β_1 and β_2 could suffer from reverse causality or omitted variables bias. We address this possibility by testing for three possible alternative explanations. The first possibility is reverse causality: that randomly occurring differences between the math ability of boys and girls in a given classroom affects parent beliefs. The second is a flavor of the "reflection problem" in which parents' beliefs could be affected by the beliefs of other parents in their child's randomly assigned classroom. The third is that the gender of the math teacher the child is randomly assigned to may also affect parent beliefs about the relative math ability of boys and girls.

We first describe and present a series of tests for the possibility that parents may adjust their beliefs after viewing the (relative) math ability of girls and boys among their child's peers, i.e., reverse causality. Using our main estimating equation, we design two empirical tests for this possibility. In both tests, the dependent variable is a dummy for whether the parent believes $B_m > G_m$. In the first test, our main explanatory variable is the difference between the math test scores of the child's peer boys and peer girls. This test estimates how an increase in the math performance of boys (relative to girls) among the children in a child's classroom affects the beliefs of the child's own parent. In the second test, we create a dummy variable equal to one if the highest performing child in the class is male. This tests for the informational salience that comes with the recognition top performers are often given, and the potential for this to have asymmetric effects by gender (Cools et al., 2019).

In Panel A of Table 7, we present our results for the effect of an increase in boys' performance, relative to girls, on a parent's beliefs. We find no evidence that a parent is more likely to believe $B_m > G_m$ when their child is assigned to a classroom where boys outperform girls in math. Our estimated coefficients are small and not distinguishable from zero, but also precise: we can reject that a 0.1 SD increase in peer boys' performance, relative to peer girls, generates anything larger than a 0.8 percentage point change in the likelihood that a parent believes boys are better than girls at learning math (from a baseline of 41%). In Columns 2 and 3, we estimate these effects separately for parents of seventh graders and ninth graders. Recall that the seventh grade children of these parents have been with their peers for three to six months when the parent is interviewed, and the ninth grade children have been with their same peer group for two years and three to six months. This analysis tests for the possibility that, as the amount of time parents are exposed to their child's peers increases, so will the likelihood they update their beliefs. Our coefficient estimates provide no evidence of this phenomenon either. In Panel B, we present analog results using a dummy for the top scoring student on the midterm math test being male as the main explanatory variable. We see no evidence of parents' beliefs changing in response to the gender of the top performer. Our results suggest that even a large change in the relative performance of boys and girls in math among a child's peers, or a change in the gender of the top performer in math, is unlikely to generate more than a very small change in parent beliefs.[22]

Next, we test whether parent beliefs adjust in response to exposure to other parent beliefs; this is a specific flavor of the "reflection problem" studied in Manski (1993) and Angrist (2014). To test for this, we regress peer parent beliefs on own parent beliefs using our core specification. Note that regressing an individual's given characteristic (own parent's beliefs) on the leave-one-out average of this same characteristic (peer parent beliefs) in an individual's randomly assigned cluster yields a mechanical negative correlation. The intuition behind this is as follows: given the random assignment of students into classes, the law of large numbers predicts that, in a given class, the proportion of students with a certain characteristic (e.g., average parent beliefs or percent female) will be distributed normally. A student's characteristic is thus negatively correlated with the leave-one-out average because the proportion (including the student herself) is equivalent to the sum of the student's characteristic and this average.

To formalize this intuition, we conduct a permutation test, randomly assigning to each child 1,000 "placebo own parent belief" random variables with the same potential values (0/1) and expected value (0.410) as the true parent belief variable. We generate 1,000 new "placebo peer parent beliefs" measures, using the 1,000 placebo belief draws for the parents of each student's peers in their classroom. We standardize these and then run one regression for each of the 1,000 draws, regressing the random variable of each student's own parent's placebo beliefs on the placebo peer parent beliefs measure, its interaction with

[22] We find similar results using the proportion of the top three students in the class who are male; results available on request.

Table 7: Estimating the extent to which a parent's beliefs change in response to an increase in boys' relative performance among their child's peers

	Dependent variable:		
	Parent believes boys are better than girls at learning math		
	(1)	(2)	(3)
Panel A: Gender gap in peer test scores			
Gender gap in child's peers' test scores	0.004	0.004	0.002
	(0.003)	(0.004)	(0.005)
Gender gap in child's peers' test scores x own child is female	-0.002	-0.006	0.005
	(0.003)	(0.004)	(0.003)
Mean in sample	0.409	0.394	0.441
Number of observations	8,028	5,428	2,600
Panel B: Top student in class is male			
Top student in class is male	0.023	0.021	0.006
	(0.019)	(0.023)	(0.042)
Top student in class is male x own child is female	-0.004	-0.008	0.011
	(0.016)	(0.020)	(0.030)
Mean in sample	0.409	0.394	0.441
Number of observations	8,228	5,553	2,675
Sample			
Grade seven	X	X	
Grade nine	X		X

Note: this table presents a series of tests for the possibility that parent beliefs are affected by the relative performance in math of boys and girls among their child's (randomly assigned) classroom peers. In Panel A, we generate a leave-one-out measure of the difference between boys' and girls' test scores in the midterm math exam for the child's peers in their randomly assigned classroom. Using the specification in Equation 1, we regress the child's parent's likelihood of believing boys are better than girls at learning math on this measure. In Panel B, we generate an indicator function equal to one if, in the child's class, a boy earns the top midterm math test score, and regress the child's parent's beliefs on it. We find similar results using the proportion of the top three students in the class who are male (results available upon request).

the female dummy, and the other controls as given in our estimating equation. This generates $\tilde{\gamma}$, the mean of our permutation test estimates. We find $\tilde{\gamma} = -0.107$ ($SE = 0.026$). Using the true data, we estimate $\hat{\gamma}$, the effect of a one SD increase in the proportion of peers whose parents believe $B_m > G_m$ on a child's own parent's likelihood of holding the belief, to be $\hat{\gamma} = -0.072$. Because our estimate of $\hat{\gamma}$ falls well within the 95% confidence interval around $\tilde{\gamma}$ generated by the permutation test, we conclude there is no evidence of this reflection problem.

We test whether the random assignment of teacher gender to child gender affects a parent's likelihood of believing $B_m > G_m$. Here again we can simply regress the parent's response to the belief question on the gender of the math teacher, controlling for grade-by-school fixed effects. We find no evidence of this potential channel either. The estimated coefficient of the impact on the likelihood a parent believes $B_m > G_m$ of their child being assigned a female math teacher is small (0.02) and statistically insignificant (standard error: 0.018). We also find no evidence of differential effects for parents of seventh and ninth grade students.

Finally, we comment on the extent to which parents may update their beliefs in response to their own child's gender and ability. We cannot empirically evaluate the extent to which a child's own ability affects their parents' beliefs about the relative ability of boys and girls in math.[23] We assume, however, that the primary interaction between parents and their child is parents' beliefs and actions shaping those of their children, and not child ability shaping parent beliefs. This assumption is based on three arguments: one, the vast child development literature documenting the great extent to which parents influence their children's development (c.f., Siegler et al., 2003); two, the argument we make earlier in this paper about how parents' beliefs are relatively harder to manipulate than children's because of the longer time over which they have been formed; and three, the fact that even if child ability were to affect parent beliefs, we show in the next subsection that controlling for peer cognitive ability does not substantially change our belief transmission results or the estimated effects on test scores.[24]

We argue that these patterns are best explained by the fact that parent beliefs are well-formed by the time their child enters middle school. While early in life, a person's beliefs are malleable, as they age their

[23] This is because we lack panel data on the child's ability and their parents' beliefs from earlier in the child's life.

[24] We can also measure how parent beliefs about gender differences in math ability vary with the gender of their child(ren). The revelation of child gender is potentially a large information shock, especially in China, where son preference often prevails. More than half of the families in our sample have multiple children. On average, among parents who have only girls, 38.0 percent believe $B_m > G_m$; among parents who have both, 40.8 percent hold the belief; among parents with only boys, 43.7 percent do. The correlation between child gender and parent beliefs is small compared to the idiosyncratic variation in parent beliefs across classrooms. We interpret this as further evidence of our claim that beliefs about gender differences in math ability are much more likely to shift in childhood than in adulthood.

cumulative exposure to the world increases and their beliefs become firmer. The beliefs of the parents of the middle school students in our sample have been influenced by 35-50 years' worth of cumulative information. Because of this greater exposure, we would expect parents' beliefs to be firmer, and thus harder to change, than children's.

5.2 Interpreting our estimates

This section addresses two questions. First, is the transmission of beliefs we study separate from, or consistent with, other sources of peer effects? Second, what can we say about the potential for direct interaction between peer parents and the child - as opposed to from peer parents to the peer and then on to the child - in driving our results?

There are two potential explanations for the main patterns we find. One is that the effects we measure are primarily the result of the intergenerational transmission of beliefs about differential gender ability in math. The other is that these effects are instead just a novel measure of some other, broader latent peer effect, perhaps similar to the peer effects captured using measures of peer ability or peer socioeconomic status (c.f., Sacerdote et al., 2011; Feld and Zölitz, 2017; Fruehwirth and Gagete-Miranda, 2019). To disentangle these two possible mechanisms, we conduct a series of horse race regressions where we add controls for other variables known to generate peer effects in prior work and study how our coefficient estimates change. These other sources of peer effects include various traits of peers' parents, including education, income, and family background (Fruehwirth and Gagete-Miranda, 2019; Chung, 2018); the gender composition of the child's classroom (Hu, 2015); and peers' cognitive ability (c.f. Sacerdote et al., 2011; Feld and Zölitz, 2017).

Our main approach adds controls for these various sources, one at a time, and examines the extent to which the magnitude and precision of our estimates of β_1 and β_2 for child beliefs and math test scores vary. Should the estimates decrease substantially in magnitude or precision, this would be evidence that our measure of peer parent beliefs is a good proxy for other peer effects, but also that there is less reason to believe that peer parent beliefs are a separate contributor to the peer effects we measure here. On the other hand, if the magnitude and precision of these estimates persist after adding controls for other known contributors of peer effects, this would tell us that variation in peer parent beliefs, independent of these other known peer effect sources, is driving the results presented in Section 4.

The sources we consider are peer parents' education, income, and family background; peer gender composition; and peer ability. For peer parents' education, we add variables capturing the average number of years the child's peers' mothers and fathers spent in school, respectively. For income, we add the proportion of peers who fall in the "low income" category according to the school. For family background status, we use the proportion of peers with a rural residence permit, or hukou, following Chung (2018). The proportion of girl peers in the child's classroom is self-explanatory. The cognitive ability measure is from a proprietary test designed by the CEPS team using items similar to those in a Raven's Matrices test, standardized to be mean 0, SD 1. We add each of these controls, and the interaction between the control and the child's gender, one source at a time, to see how their inclusion affects our estimates of the impact of exposure to peers whose parents believe $B_m > G_m$.

We present the results of this test in Table 8. Panel A shows that our estimates of the effects of exposure to more peers whose parents believe $B_m > G_m$ on a child's beliefs vary little with the inclusion of additional controls for various peer parent traits, the gender composition of the classroom, and the average cognitive ability of peers. Panel B shows similar results for the stability of our estimates for math test scores. We interpret these patterns as evidence that the transmission of beliefs from parents to children and on to their peers, and not the other important peer effect mechanisms, generate most of the effects of exposure to this type of peers on child beliefs and girls' relative math performance that we estimate in Section 4.

In Tables A.6-A.10 we provide several alternative versions of this table. Table A.6 shows these estimates when the own parent beliefs variables (OPB and OPB x female) are removed from the estimating equation. Table A.7 shows these estimates for girl peer parents' beliefs using the original covariates, and Table A.8 shows the girl peer parents' beliefs estimates when the own parent beliefs variables are removed from the right hand side. Tables A.9 and A.10 show these same analyses, respectively, but using boy peer parents' beliefs. The patterns they display are similar to those in Tables 3 and A.4: removing own parent beliefs dampens the estimates of the effect of exposure to all peers whose parents believe $B_m > G_m$ on child beliefs, but amplifies them for the homophily results, particularly for girls. Overall, these results show that exposure to more peers whose parents hold this belief has robust, independent effects on child beliefs and math test scores.

Another question of interest is the relative importance of two potential channels of peer parent belief transmission to children: one, from peers' parents directly to the child herself; two, from the peers' parents to the peer, and then from the peer to the child. Olivetti et al. (Forthcoming) show that the direct channel is an important factor in shaping US girls' beliefs about their place in the labor market. The only related

Table 8: Disentangling the effects of exposure to peers whose parents believe $B_m > G_m$ and other sources of peer effects

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A outcome: Believes boys are better than girls at learning math						
Peer parent beliefs (PPB)	0.046***	0.043***	0.043***	0.041***	0.041***	0.038***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
PPB x female	0.002	0.005	0.007	0.007	0.006	0.012
	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)
R-squared	0.167	0.168	0.169	0.169	0.169	0.170
Number of observations	8,057	8,057	8,057	8,057	8,057	8,057
Panel B outcome: Midterm math test score						
Peer parent beliefs (PPB)	0.039	0.027	0.035	0.033	0.033	0.030
	(0.039)	(0.036)	(0.035)	(0.035)	(0.035)	(0.034)
PPB x female	-0.057**	-0.049**	-0.050**	-0.049*	-0.051**	-0.045*
	(0.025)	(0.024)	(0.025)	(0.025)	(0.025)	(0.026)
R-squared	0.193	0.197	0.198	0.198	0.198	0.199
Number of observations	8,028	8,028	8,028	8,028	8,028	8,028
Specification						
Baseline controls	X	X	X	X	X	X
Peers' parents' education		X	X	X	X	X
Peers' parents' income			X	X	X	X
Peers' parents' hukou status				X	X	X
Proportion of peers female					X	X
Peers' cognitive ability scores						X

Note: this table shows a series of horse-race regressions, including additional independent variables as listed in the "specification" legend at the bottom of the table, to assess the relative importance of peer parent beliefs and other determinants of peer effects in generating our estimates from Tables 4 and 6. The dependent variable in Panel A is coded as 0 = No, 1 = Yes (mean 0.526), and, in Panel B, the test score variable is in standardized SD units. There are 8,057 observations in the Panel A regressions and 8,028 in those of Panel B. In Table A.6, we show the analog to these results generated without own parent beliefs on the right hand side.

datapoint collected in the CEPS is each parent's response to the following yes/no question: "do you know the friends that your child often spends time with?" A high proportion – 87.8 percent of parents – respond "yes" to this question. In the appendix, we describe our attempts to study the relative importance of the two channels. We find that using this interaction to estimate whether peer parents who know their children's friends have greater transmission of beliefs has no more descriptive power than using a random sample of an equal proportion of parents (who may or may not interact with their children's friends). Given the flaws of this particular measure, we argue that this test is inconclusive.

The analyses from this section suggest that our estimates of β_1 and β_2 capture the impact of being exposed to a greater proportion of peers whose parents believe that boys are inherently better than girls at learning mathematics. In Section 5.1 we see that parent beliefs appear to be stable to various factors that change with random assignment of their child to a classroom. In Section 5.2, we see that there is sufficient variation in the parent beliefs measure, independent of other well-known sources of peer effects, to generate the majority of the relationships that we show in Section 4.

Nonetheless, the relationships captured in our estimates of β_1 and β_2 are "messy." They comprise both the causal linkage from parent beliefs to child beliefs, and on to the child's peers, as well as any impact from the family-level unobservables that may lead to both differences in parent beliefs and some unobservable child trait that influences the outcomes of the child's peers. Our measure of peer parent beliefs is agnostic about the relative contribution of these two sources. Rather, the results establish that the broader channel, measuring the effects coming from everything captured in the peer parent beliefs measure, is a meaningful contributor to child beliefs and outcomes. Furthermore, effects coming from this channel appear to be largely independent of the myriad other sources of peer effects studied in previous work.

6 Heterogeneity and further impacts on girls

In this section, we conduct a series of analyses to investigate potential heterogeneity in the effects of exposure to peers whose parents believe that boys are better than girls at learning math. We also provide a richer characterization of how this exposure affects girls' beliefs, aspirations, and performance in school.

6.1 Heterogeneity analyses

In this subsection we estimate the relationship between duration of exposure to peers and effect size and, separately, evaluate whether the effect of exposure to peers whose parents believe that boys are better than girls at learning math varies by a child's own parent's reported beliefs.

We have two sets of children in our data – seventh graders, who have been with their peers for three to six months when interviewed, and ninth graders, who have been with their peers for two more years than the seventh graders. Economic intuition generates disparate predictions for how increases in the duration of exposure to peers may condition our estimates for child beliefs and performance.

For beliefs, there are two predictions which point in opposite directions. Prediction one is consistent with a simple model of Bayesian updating. A child's priors are particularly ripe for updating when they enter the seventh grade and encounter a large increase in the difficulty of the math curriculum. The child updates their priors based on the new information they are confronted with – the curriculum, the overall middle school environment, and the information conveyed to them by their peers. Once that information is incorporated into the child's posterior, it is no longer "new" to them, and so we would expect only small subsequent changes in beliefs as exposure lengthens. Prediction two is that learning from peers may be a slow or iterative process, and so we would expect to see larger belief changes among the ninth graders than among the seventh graders (Bénabou and Tirole, 2016).

For test scores, the predictions are clearer. Our intuition here comes from the fact that learning builds on itself. Initially, exposure to the belief $B_m > G_m$ is likely to cause girls (boys) to exert marginally less (more) effort or enthusiasm for math, which leads to marginally worse (better) performance. This performance signal then provides information about the returns to subsequent effort, which can affect future enthusiasm/effort allocation decisions and lead to a cycle of effects compounding over time. This predicts larger effects in tests scores for ninth graders than for seventh graders (Cunha and Heckman, 2009; Genicot and Ray, 2017).

In Table 9, we present grade-specific coefficient estimates for four outcomes – believing that boys are better than girls at learning math, perceiving the current math class to be difficult, educational aspirations, and the child's standardized midterm math test score.[25] For the beliefs estimates, our results are indetermi-

[25] As discussed in Footnote 9 and shown in Table A.2, the schools in our estimation sample with and without grade 9 classrooms that maintain the randomization initiated in grade 7 are balanced on most observable characteristics. Table A.12 shows the same analyses as given in Table 9, but restricting the sample to only schools which have grade 9 classrooms that maintain the randomization. The two sets of results are very similar.

Table 9: Effect size by duration of exposure to peers

	Believes boys are better than girls at learning math		*Perceived difficulty of current math class*		*Aspires to earn BA*		*Midterm math test score*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Grade 7	Grade 9	Grade 7	Grade 9	Grade 7	Grade 9	Grade 7	Grade 9
Peer parent beliefs (PPB)	0.032*	0.034**	0.007	-0.028	0.001	0.007	0.044	0.046
	(0.019)	(0.017)	(0.020)	(0.020)	(0.026)	(0.016)	(0.058)	(0.032)
PPB x female	-0.004	0.025	0.012	0.029**	0.010	0.018	-0.027	-0.089***
	(0.020)	(0.020)	(0.013)	(0.015)	(0.011)	(0.016)	(0.031)	(0.030)
Own parent beliefs (OPB)	0.271***	0.299***	-0.058***	-0.076***	0.011	0.033	0.181***	0.135***
	(0.019)	(0.028)	(0.020)	(0.029)	(0.018)	(0.023)	(0.031)	(0.050)
OPB x female	0.026	0.032	0.135***	0.187***	-0.003	-0.032	-0.277***	-0.291***
	(0.026)	(0.033)	(0.028)	(0.040)	(0.027)	(0.030)	(0.052)	(0.064)
Female	-0.099	0.293**	-0.330***	0.155	0.449***	0.374***	0.591**	1.087***
	(0.164)	(0.141)	(0.121)	(0.128)	(0.127)	(0.147)	(0.289)	(0.365)
Mean in sample	0.504	0.572	0.546	0.619	-	-	-	-
Observations	5,414	2,643	5,538	2,674	5,509	2,664	5,428	2,600

Note: this table presents results for the effect of exposure to peers whose parents believe $B_m > G_m$ on children's beliefs and performance, estimated separately for those in grade seven and those in grade nine. The dependent variables are labeled above the column numbers here. In Columns 1, 2, 5, and 6, the dependent variable is coded as 0 = No, 1 = Yes. In Columns 3 and 4, the dependent variable is coded as 0 for low perceived difficulty and 1 for high perceived difficulty. In Columns 7 and 8, the dependent variable is continuous with SD = 1. In Table A.11, we show the analog to these results generated without own parent beliefs on the right hand side. Table A.12 shows the analysis with own parent beliefs included, but restricting our sample to only schools which have grade 9 classrooms that maintain the random sorting assigned in grade 7.

nate for boys: none of the coefficient estimates for seventh grade children are statistically distinguishable from those for ninth grade children. For girls, the magnitude of the overall effect ($\beta_1 + \beta_2$) suggests the effects may grow over time. As predicted, for both boys and girls we estimate that the effects of exposure to peers whose parents believe $B_m > G_m$ on math test scores and perceived difficulty of math increase as the duration of exposure increases. We continue to see no effects for aspirations.

Do the effects of exposure to peers whose parents believe $B_m > G_m$ vary by the beliefs the child is exposed to in their own home? To answer this question, we add two variables to our estimating equation: the interaction of peer parent beliefs and own parent beliefs, and this variable's interaction with the child's gender. We present our results in Panel A of Table 10. We find that increased exposure to peers whose parents believe that boys are better than girls at learning math appears to generate greater harms for girls whose parents also hold this belief, both in terms of the likelihood of the child holding that belief herself and her performance in mathematics. The standard errors in this analysis are large, however, suggesting that adding further interaction terms to our main specification pushes the limits of what we can precisely estimate using this estimation strategy on a dataset with this sample size.[26] We see no evidence of heterogeneity in effects on perceived difficulty of math or aspirations.

6.2 How do girls respond?

This section studies the effects on girls in greater depth. First, we conduct an analysis building on the work of Lavy and Sand (Forthcoming) and Hahn et al. (Forthcoming), who show that exogenous increases in proximity to friends, either in class or in a study group, can have positive impacts on girls' academic performance. The CEPS collects information from the child on whether their five closest friends are in the same randomly assigned class as they are.[27] We add the number of friends in the class, its interactions with the child's own gender and our measure of peer parent beliefs (respectively), and the triple interaction, as additional independent variables in our estimating equation. We study the estimated coefficients on these new explanatory variables to determine whether having friends in class conditions the effects of exposure to peers whose parents believe $B_m > G_m$ on child beliefs or performance. Note that this set of results is only

[26] We also test for the possibility that the effects of exposure to peers whose parents believe $B_m > G_m$ may vary across three other predetermined child-level factors - family income, parents' education, and whether the family lives in a rural or urban area. We see no evidence of heterogeneity on any of these dimensions. For the sake of brevity, we do not include the tables in the paper, but they are available from us by request.

[27] Unfortunately, we do not have access to friends' names or links to their identifiers and so cannot link a child's list of friends to other children in our dataset.

Table 10: Heterogeneity analyses

	(1) Believes $B_m > G_m$	(2) Perceived difficulty	(3) Aspires to BA or higher	(4) Math test score
Panel A: Heterogeneity by own parent beliefs				
Peer parent beliefs (PPB)	0.055***	-0.013	0.001	0.037
	(0.015)	(0.015)	(0.019)	(0.043)
PPB x female	-0.014	0.020	0.008	-0.038
	(0.016)	(0.014)	(0.014)	(0.028)
Own parent beliefs (OPB) x PPB	-0.023	0.005	0.001	0.008
	(0.017)	(0.018)	(0.014)	(0.026)
OPB x PPB x female	0.042**	-0.002	0.001	-0.053
	(0.020)	(0.024)	(0.020)	(0.034)
OPB	0.285***	-0.065***	0.018	0.170***
	(0.016)	(0.016)	(0.014)	(0.027)
OPB x female	0.031	0.152***	-0.013	-0.292***
	(0.020)	(0.023)	(0.020)	(0.041)
Mean in sample	0.526	0.570	0.658	-
Observations	8,057	8,212	8,173	8,028
Panel B: Heterogeneity by number of friends in class				
Peer parent beliefs (PPB)	0.034*	0.008	0.003	-0.009
	(0.018)	(0.019)	(0.023)	(0.054)
PPB x female	0.018	0.009	-0.037*	-0.142**
	(0.022)	(0.022)	(0.021)	(0.061)
PPB x number of friends in class (FIC)	0.004	-0.006	-0.000	0.016
	(0.004)	(0.005)	(0.004)	(0.010)
PPB x female x FIC	-0.005	0.003	0.015***	0.028*
	(0.007)	(0.006)	(0.006)	(0.015)
FIC	0.011**	-0.009*	0.014***	0.011
	(0.005)	(0.005)	(0.004)	(0.010)
FIC x female	-0.006	-0.004	-0.010*	0.006
	(0.007)	(0.006)	(0.006)	(0.013)
Mean in sample	0.526	0.570	0.658	-
Observations	7,890	8,024	8,006	7,850

Note: this table shows two sets of heterogeneity results. In Panel A, we show analysis of how the effects of greater exposure to peers whose parents believe $B_m > G_m$ vary with own parents beliefs (OPB). In Panel B, we show analysis of how these effects vary with the number of close friends in the child's randomly assigned class (FIC). In each table, we add three interactions - the variable (OPB or FIC) interacted with the child's gender, with the peer parent belief measure, and the triple interaction. Dependent variables are given in the column headings. Differences in the number of observations between Panels A and B come from missing data on friends.

suggestive, as our survey data on the number of friends inside or outside of the class are collected during the school year. As a result, who the child regards as one of their five closest friends is potentially endogenous to other factors, such as a child's overall experience in the school and the classroom, which may also affect, or be determined by, our outcome variables.

As Panel B of Table 10 shows, the harms of exposure for girls decrease as the number of friends the child has in her class increases. Note that the PPB x female coefficients now pertain to a girl with no close friends in her class. In terms of both aspirations and math test scores (columns 3 and 4), our estimates on PPB x female suggest that these girls experience much greater harms from exposure to peers whose parents believe $B_m > G_m$ than we estimated previously. On the other hand, the addition of each close friend to the classroom decreases these harms by 20-30%, and a girl with all five closest friends in the class appears to be entirely immune to these negative effects.[28] We see no evidence of heterogeneity by the number of friends in class in our estimates for either the girl's likelihood of believing $B_m > G_m$ or her perceived difficulty of math. We also see no evidence of this heterogeneity in any of the outcomes for boys.

Related work from sociology and psychology (Wentzel, 1998; Roseth et al., 2008) suggests a possible explanation for this pattern of results: friendship may increase girls' resilience in the face of stressors, such as being told that girls (like you) are worse than boys at learning math. In this light, our findings in Table 10 may provide weak evidence of the potential for outreach to vulnerable children, particularly girls, in minimizing the harm caused by the intergenerational transmission of beliefs about the innate math ability of boys and girls.

Next, we study the effects of exposure to peers whose parents believe $B_m > G_m$ on girls' performance in other academic subjects, and their time spent on hobbies and in tutoring. Here also there are divergent predictions. Comparative advantage predicts that if girls are told they have less innate math ability than boys, girls may reallocate effort, enthusiasm, and time towards other subjects or hobbies in which they have a comparative advantage. This suggests a possible increase in performance in these subjects in response to greater exposure to the message $B_m > G_m$. Work from psychology, however, suggests that exposing girls to this type of message can cause them to have broader negative thoughts about themselves, which may decrease performance overall (Steele, 1997).

To test for this, we first look at how exposure to peers whose parents believe $B_m > G_m$ affects children's

[28]To arrive at this conclusion, we take the [peer parent beliefs x female] coefficient and add to it the [peer parent beliefs x female x number of friends in class] coefficient multiplied by five, to capture the impact of all five listed friends being in the class.

performance in Chinese and English. Our estimates reject even small gains in girls' test scores for either subject. We show these results in Table A.13. We also conduct a series of additional empirical tests to look for evidence of a reduction in enthusiasm or effort for girls. We report but do not show analysis of other outcomes potentially affected by this exposure, including girls' expressed confidence in their own future, time use (hours spent studying, in cram school, and on hobbies), or beliefs that math, English, or Chinese are helpful for their future. We find no evidence of changes in these, though our results are imprecise.[29]

7 Conclusion

In this paper, we study how beliefs about gender differences in math ability transmit across generations and how this affects children's beliefs about themselves and their academic performance. We find that exposure to peers whose parents believe that boys have greater innate math ability than girls makes a child more likely to hold this belief herself. We show that this exposure harms girls and helps boys. It affects both children's assessment of their own ability in math and their actual performance in the subject. We find that the effects of exposure to these peers is largely independent of other well-known sources of peer effects identified in the literature. We also find that these effects are strongest from exposure to peers of the same gender whose parents hold this belief, and that the test score harms we observe for girls increase with the length of time girls are exposed to their peers.

A key limitation of our approach is that we study data in the cross-section. As a result, we are unable to track the longer-term academic and career effects of exposure to these beliefs, questions of central policy concern. We also work in a setting in which girls outperform boys in math. Even in such a setting, we find harms of exposure to peers whose parents hold this belief. We suspect our estimates may be a lower bound on the harms that come from exposure to such beliefs in settings where girls perform less well than boys. This could occur, for example, if lower (perceived) ability children responded more to such exposure.

Given the importance of beliefs about one's own ability in shaping decisions and outcomes, a key problem facing policymakers in both developed and developing countries is better understanding how these beliefs are transmitted, the impacts of this transmission, and what can be done to prevent any harms that this causes. Overall, our results document that the intergenerational transmission of beliefs about gender differences in innate math ability occurs both within and across families. These results also shed light on

[29]Results available upon request.

how such beliefs are self-reinforcing through their impact both on children's beliefs about their own ability and their actual performance in mathematics.

We know much less about how to address these issues. The negative effects on girls' performance and aspirations lessen with the number of close friends the child has in their class, in line with prior work finding similar benefits to assigning girls to classes or study groups with their friends. In other work, we have shown that positive role models such as female math teachers can counter the harms that exposure to these beliefs can cause for particularly vulnerable girls (Eble and Hu, 2019). The larger problem of how to prevent the transmission of such beliefs and the harms this transmission can cause remains unresolved.

References

Ammermueller, Andreas and Jörn-Steffen Pischke, "Peer effects in European primary schools: Evidence from the progress in international reading literacy study," *Journal of Labor Economics*, 2009, *27* (3), 315–348.

Angrist, Joshua D, "The perils of peer effects," *Labour Economics*, 2014, *30*, 98–108.

Antecol, Heather, "An examination of cross-country differences in the gender gap in labor force participation rates," *Labour Economics*, 2000, *7* (4), 409–426.

_ , "Why is there interethnic variation in the gender wage gap?: The role of cultural factors," *Journal of Human Resources*, 2001, pp. 119–143.

_ , Ozkan Eren, and Serkan Ozbeklik, "The effect of teacher gender on student achievement in primary school," *Journal of Labor Economics*, 2015, *33* (1), 63–89.

Beilock, Sian L, Elizabeth A Gunderson, Gerardo Ramirez, and Susan C Levine, "Female teachers' math anxiety affects girls' math achievement," *Proceedings of the National Academy of Sciences*, 2010, *107* (5), 1860–1863.

Bénabou, Roland and Jean Tirole, "Mindful economics: The production, consumption, and value of beliefs," *Journal of Economic Perspectives*, 2016, *30* (3), 141–164.

Bian, Lin, Sarah-Jane Leslie, and Andrei Cimpian, "Gender stereotypes about intellectual ability emerge early and influence children's interests," *Science*, 2017, *355* (6323), 389–391.

Bifulco, Robert, Jason M Fletcher, and Stephen L Ross, "The effect of classmate characteristics on post-secondary outcomes: Evidence from the Add Health," *American Economic Journal: Economic Policy*, 2011, *3* (1), 25–53.

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli, and Andrei Shleifer, "Stereotypes," *Quarterly Journal of Economics*, 2016, *131* (4), 1753–1794.

Bruhn, Miriam and David McKenzie, "In pursuit of balance: Randomization in practice in development field experiments," *American Economic Journal: Applied Economics*, 2009, *1* (4), 200–232.

Carlana, Michela, “Implicit stereotypes: Evidence from teachers’ gender bias,” *The Quarterly Journal of Economics*, 2019, *134* (3), 1163–1224.

Carrell, Scott E and Mark L Hoekstra, “Externalities in the classroom: How children exposed to domestic violence affect everyone’s kids,” *American Economic Journal: Applied Economics*, 2010, *2* (1), 211–28.

Chen, Xi and Suqin Ge, “Social norms and female labor force participation in urban China,” *Journal of Comparative Economics*, 2018, *46* (4), 966–987.

Chung, Bobby, “Peers Parents and Educational Attainment,” *Mimeo, Clemson University*, 2018.

Cools, Angela, Raquel Fernández, and Eleonora Patacchini, “Girls, Boys, and High Achievers,” *NBER Working Paper 25763*, 2019.

Cunha, F. and J.J. Heckman, “The Economics and Psychology of Inequality and Human Development,” *Journal of the European Economic Association*, 2009, *7* (2), 320.

Currarini, Sergio, Matthew O Jackson, and Paolo Pin, “An economic model of friendship: Homophily, minorities, and segregation,” *Econometrica*, 2009, *77* (4), 1003–1045.

de San Román, Ainara González and Sara de la Rica Goiricelaya, “Gender Gaps in PISA Test Scores: The Impact of Social Norms and the Mother’s Transmission of Role Attitudes,” *Estudios de Economía Aplicada*, 2016, *34*, 79–108.

Dee, Thomas S, “Teachers and the gender gaps in student achievement,” *Journal of Human Resources*, 2007, *42* (3), 528–554.

Dhar, Diva, Tarun Jain, and Seema Jayachandran, “Intergenerational Transmission of Gender Attitudes: Evidence from India,” *The Journal of Development Studies*, 2018, pp. 1–21.

Eble, Alex and Feng Hu, “Child beliefs, societal beliefs, and teacher-student identity match,” *CDEP-CGEG Working Paper 43*, 2019.

Ellison, Glenn and Ashley Swanson, “The gender gap in secondary school mathematics at high achievement levels: Evidence from the American Mathematics Competitions,” *Journal of Economic Perspectives*, 2010, *24* (2), 109–128.

Feld, Jan and Ulf Zölitz, "Understanding peer effects: On the nature, estimation, and channels of peer effects," *Journal of Labor Economics*, 2017, *35* (2), 387–428.

Fruehwirth, Jane Cooley and Jessica Gagete-Miranda, "Your peers' parents: Spillovers from parental education," *Economics of Education Review*, 2019, *73*, 101910.

Genicot, Garance and Debraj Ray, "Aspirations and Inequality," *Econometrica*, 2017, *85* (2), 489–519.

Gong, Jie, Yi Lu, and Hong Song, "The effect of teacher gender on students' academic and noncognitive outcomes," *Journal of Labor Economics*, 2018, *36*, 743–778.

Hahn, Youjin, Asad Islam, Eleonora Patacchini, and Yves Zenou, "Do friendship networks improve female education?," *Economic Journal*, Forthcoming.

Hansen, Ben B and Jake Bowers, "Covariate balance in simple, stratified and clustered comparative studies," *Statistical Science*, 2008, pp. 219–236.

He, Leshui, Stephen L Ross et al., "Classroom peer effects and teachers: Evidence from quasi-random assignment in a Chinese middle school," *Human Capital and Economic Opportunity Global Working Group Working Paper 2017-014*, 2017.

Hu, Feng, "Do girl peers improve your academic performance?," *Economics Letters*, 2015, *137*, 54–58.

Jain, Tarun and Mudit Kapoor, "The impact of study groups and roommates on academic performance," *Review of Economics and Statistics*, 2015, *97* (1), 44–54.

Jayachandran, Seema, "The roots of gender inequality in developing countries," *Annual Review of Economics*, 2015, *7* (1), 63–88.

Lavy, Victor and Analia Schlosser, "Mechanisms and impacts of gender peer effects at school," *American Economic Journal: Applied Economics*, 2011, *3* (2), 1–33.

— **and Edith Sand**, "The effect of social networks on students' academic and non-cognitive behavioral outcomes: Evidence from conditional random assignment of friends in school," *Economic Journal*, Forthcoming.

Manski, Charles F, "Identification of endogenous social effects: The reflection problem," *The review of economic studies*, 1993, *60* (3), 531–542.

Muralidharan, Karthik and Ketki Sheth, "Bridging education gender gaps in developing countries: The role of female teachers," *Journal of Human Resources*, 2016, *51* (2), 269–297.

Niederle, Muriel and Lise Vesterlund, "Explaining the gender gap in math test scores: The role of competition," *Journal of Economic Perspectives*, 2010, *24* (2), 129–144.

Nollenberger, Natalia, Núria Rodríguez-Planas, and Almudena Sevilla, "The math gender gap: The role of culture," *American Economic Review*, 2016, *106* (5), 257–61.

OECD, *The ABC of gender equality in education: Aptitude, behaviour, confidence*, OECD Publishing, 2015.

Olivetti, Claudia, Eleonora Patacchini, Yves Zenou et al., "Mothers, peers and gender identity," *Journal of the European Economic Association*, Forthcoming.

Qian, Nancy, "Missing women and the price of tea in China: The effect of sex-specific earnings on sex imbalance," *The Quarterly Journal of Economics*, 2008, *123* (3), 1251–1285.

Rodríguez-Planas, Núria and Natalia Nollenberger, "Let the girls learn! It is not only about math...it's about gender social norms," *Economics of Education Review*, 2018, *62*, 230 – 253.

_, Anna Sanz de Galdeano, and Anastasia Terskaya, "Independent Thinking and Hard Working, or Caring and Well Behaved? Short-and Long-Term Impacts of Gender Identity Norms," *IZA Discussion Paper Number 11694*, 2018.

Roseth, Cary J, David W Johnson, and Roger T Johnson, "Promoting early adolescents' achievement and peer relationships: The effects of cooperative, competitive, and individualistic goal structures.," *Psychological Bulletin*, 2008, *134* (2), 223–246.

Sacerdote, Bruce et al., "Peer effects in education: How might they work, how big are they and how much do we know thus far," *Handbook of the Economics of Education*, 2011, *3* (3), 249–277.

Siegler, Robert S, Judy S DeLoache, and Nancy Eisenberg, *How children develop*, Macmillan, 2003.

Steele, Claude M, "A threat in the air: How stereotypes shape intellectual identity and performance.," *American Psychologist*, 1997, *52* (6), 613–629.

Tsui, Ming, "Gender and mathematics achievement in China and the United States," *Gender Issues*, 2007, *24* (3), 1–11.

Wang, Haining, Zhiming Cheng, and Russell Smyth, "Do migrant students affect local students' academic achievements in urban China?," *Economics of Education Review*, 2018, *63*, 64–77.

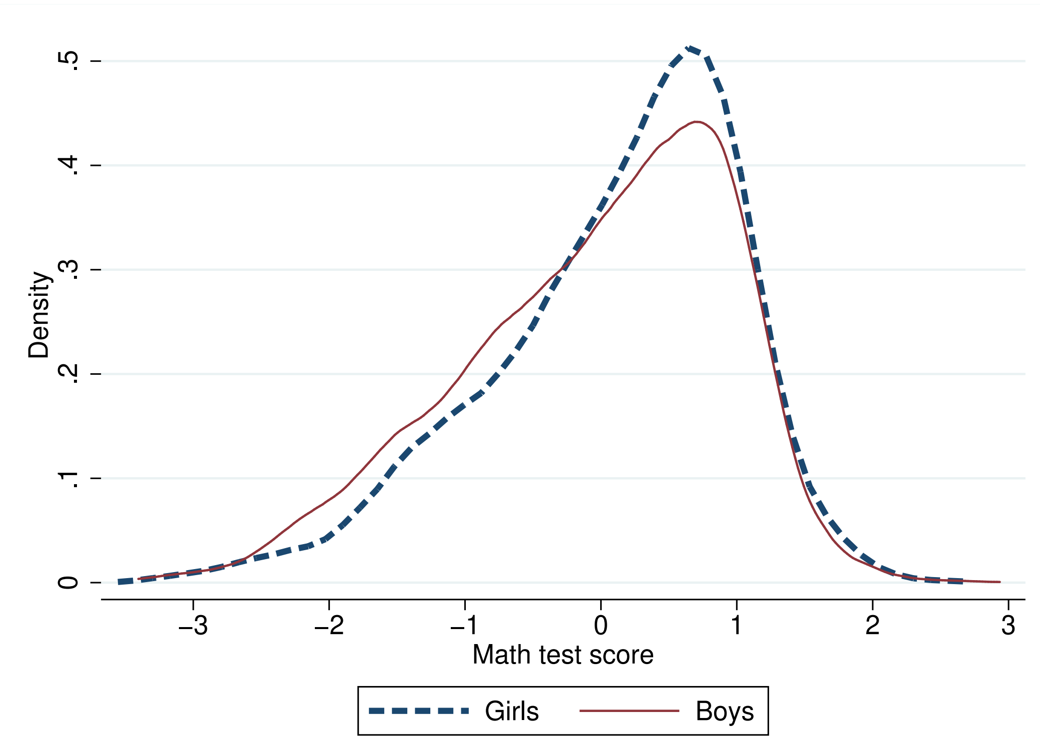
Wentzel, Kathryn R, "Social relationships and motivation in middle school: The role of parents, teachers, and peers.," *Journal of Educational Psychology*, 1998, *90* (2), 202–209.

Zimmerman, David J, "Peer effects in academic outcomes: Evidence from a natural experiment," *Review of Economics and Statistics*, 2003, *85* (1), 9–23.

Appendix - for online publication only

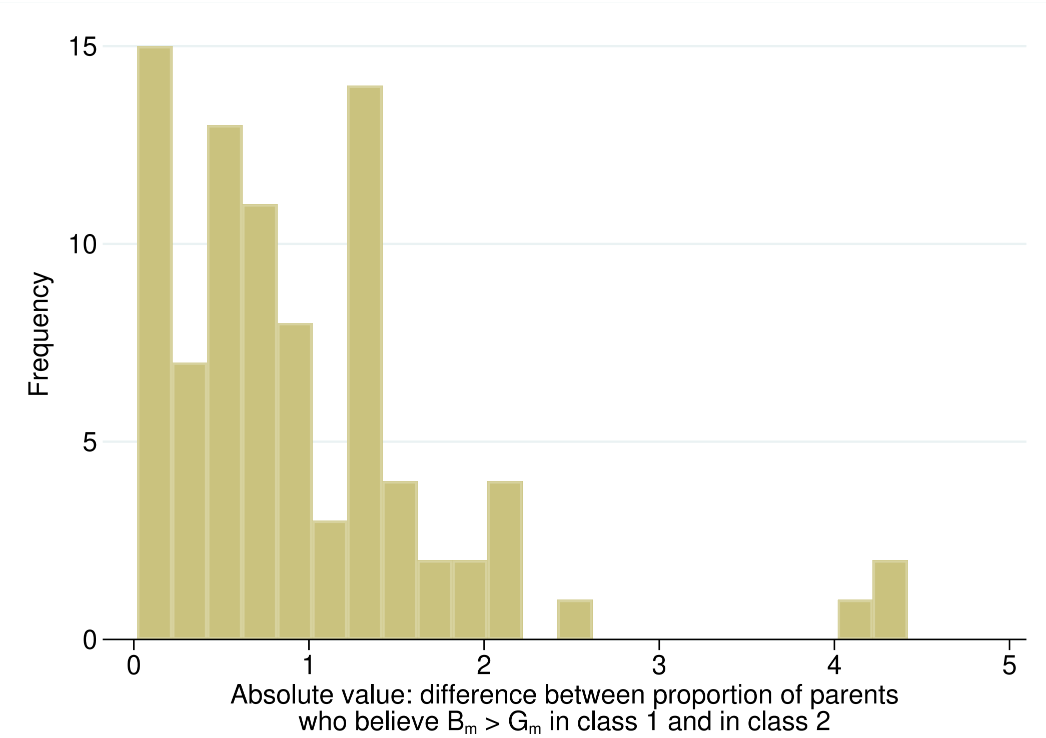
Appendix figures

Figure A.1: Distribution of test scores, by gender



Note: this figure shows the distribution of standardized math test scores for all children in our estimation sample, separately by gender.

Figure A.2: Distribution of difference between average parent beliefs in within-school, within-grade class pairs



Note: this shows the distribution of the value $\| Beliefs_{c_1} - Beliefs_{c_2} \|$ across our 86 within-school, within-grade class pairs, where $Beliefs_{c_x}$ is the mean of all parents' responses to the question "do you believe that boys are better than girls at learning math" in class x.

Appendix tables

Table A.1: Balancing test conducted separately by grade

	(1) Grade 7	(2) Grade 9
Age	-0.075***	-0.006
	(0.029)	(0.013)
Holds agricultural hukou	-0.075	-0.017
	(0.066)	(0.036)
Number of siblings	-0.087**	-0.001
	(0.040)	(0.020)
Household is poor	-0.019	0.047
	(0.064)	(0.042)
Female	0.021	0.023
	(0.027)	(0.024)
Mother's highest credential		
Middle school	0.006	0.029
	(0.020)	(0.025)
High/technical school	0.008	0.068
	(0.022)	(0.054)
College or above	0.026	0.017
	(0.028)	(0.046)
Father's highest credential		
Middle school	-0.005	0.021
	(0.024)	(0.025)
High/technical school	0.000	0.021
	(0.036)	(0.058)
College or above	-0.008	0.076
	(0.036)	(0.075)
Ethnic minority	0.015	-0.063
	(0.023)	(0.050)
Number of observations	6,040	2,924
R-squared	0.73	0.60
Joint test F-statistic	0.68	1.22
[p-value]	[0.77]	[0.30]

Note: this table presents a balancing test, as in Antecol et al. (2015), which tests for our set of predetermined characteristics' joint ability to predict the peer parent beliefs measure. Column 1 presents the results for seventh graders and Column 2 presents those for ninth graders. Both regressions include grade-by-school fixed effects. The variables are all coded as 0 = No, 1 = Yes, except for age and number of siblings. The dependent variable, peer parent beliefs, is standardized to be mean 0, SD 1.

Table A.2: Characteristics of schools with and without randomized ninth grade classrooms

	(1) Full sample	(2) Ninth graders still randomly assigned	(3) Ninth graders not randomly assigned	(4) Difference (column 1 - column 2)	(5) P-value
Private school	0.09	0.10	0.09	0.01	0.89
Total number of students in the school	1025	1118	947	171	0.29
School ranking	3.95	4.12	3.80	0.32	0.05
Proportion of teachers with BA	0.81	0.76	0.86	-0.10	0.27
Number of teachers	87	89	86	—	—
Number of observations	86	41	45	—	—

Note: this table gives summary statistics of schools with and without ninth grade classrooms that maintain the randomization established in seventh grade. The only significant difference is that schools without ninth grade classrooms that maintain randomization are slightly higher ranked than schools who do have such classrooms. This pattern is consistent with the pattern that re-sorting of children by ability is regarded as a way for middle schools to improve the likelihood of sending top children to higher-ranked high schools, and school ranking partly reflects this placement record.

Table A.3: Analog to Table 4 - effects on beliefs

	(1) Believes boys are better than girls at learning math	(2) Perceives current math class to be difficult	(3) Aspires to complete at least a BA
Peer parent beliefs (PPB)	0.021	-0.018	0.002
	(0.016)	(0.014)	(0.017)
PPB x female	0.003	0.028***	0.004
	(0.015)	(0.009)	(0.010)
Female	-0.130***	0.025**	0.128***
	(0.018)	(0.011)	(0.011)
Mean in sample	0.526	0.570	0.658
Observations	8,709	8,885	8,845

Note: this table is the analog to Table 4 but excluding the own parent beliefs variable and its interaction with student gender from the right hand side of the estimating equation. It shows results from estimating equation 1 using the dependent variable named in the column heading and described in the text. Variation in the number of observations across columns stems from differences in missing values for the dependent variables. The dependent variables are coded as 0 = No, 1 = Yes.

Table A.4: Analog to Table 5 - homophily in the transmission of beliefs

	Girl peers' parents' beliefs		*Boy peers' parents' beliefs*	
	(1)	(2)	(3)	(4)
	Believes boys are better than girls at learning math	Perceives math to be difficult	Believes boys are better than girls at learning math	Perceives math to be difficult
Gender-specific peer parent beliefs (PPB)	-0.007	-0.010	0.036***	-0.008
	(0.017)	(0.014)	(0.014)	(0.012)
Gender-specific PPB x female	0.033***	0.027***	-0.022	0.012
	(0.014)	(0.011)	(0.014)	(0.008)
Female	-0.135***	0.052**	-0.129***	0.053**
	(0.030)	(0.025)	(0.030)	(0.025)
Mean in sample	0.526	0.570	0.526	0.570
Observations	8,364	8,534	8,365	8,535

Note: this table is the analog to Table 5 generated by excluding the own parent beliefs variable and its interaction with student gender from the right hand side of the estimating equation. It shows results from estimating equation 1 using the gender-specific peer parent beliefs measure named in the first heading and the dependent variable named in the column heading (and described in the text). Variation in the number of observations across columns stems from differences in missing values for the dependent variables. The dependent variables are coded as 0 = No, 1 = Yes.

Table A.5: Analog to Table 6 - effects on performance

	(1) All peers' parents' beliefs	(2) Boy peers' parents' beliefs	(3) Girl peers' parents' beliefs
Peer parent beliefs (PPB)	0.045	0.074**	-0.040
	(0.040)	(0.037)	(0.038)
PPB x female	-0.080***	-0.053**	-0.049*
	(0.026)	(0.026)	(0.027)
Female	0.241***	0.235***	0.235***
	(0.052)	(0.051)	(0.050)
Observations		8,334	

Note: this table is the analog to Table 6 generated by excluding the own parent beliefs variable and its interaction with student gender from the right hand side of the estimating equation. In all regressions, the dependent variable is the student's test score on a midterm math test (standardized to be mean 0 SD 1).

Table A.6: Analog to Table 8 - horse race regressions after removing own parent beliefs

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A outcome: Believes boys are better than girls at learning math						
Peer parent beliefs (PPB)	0.022	0.019	0.016	0.014	0.014	0.010
	(0.017)	(0.016)	(0.017)	(0.017)	(0.016)	(0.017)
PPB x female	0.003	0.005	0.006	0.006	0.005	0.013
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)
R-squared	0.083	0.085	0.086	0.086	0.087	0.089
Number of observations	8,057	8,057	8,057	8,057	8,057	8,057
Panel B outcome: Midterm math test score						
Peer parent beliefs (PPB)	0.044	0.031	0.038	0.037	0.037	0.034
	(0.039)	(0.036)	(0.035)	(0.035)	(0.035)	(0.034)
PPB x female	-0.071***	-0.064***	-0.064***	-0.063***	-0.065***	-0.059**
	(0.025)	(0.025)	(0.025)	(0.025)	(0.026)	(0.026)
R-squared	0.188	0.192	0.193	0.193	0.193	0.194
Number of observations	8,028	8,028	8,028	8,028	8,028	8,028
Specification						
Baseline controls	X	X	X	X	X	X
Peers' parents' education		X	X	X	X	X
Peers' parents' income			X	X	X	X
Peers' parents' hukou status				X	X	X
Proportion of peers female					X	X
Peers' cognitive ability scores						X

Note: this table is the analog to Table 8 generated by excluding the own parent beliefs variable and its interaction with student gender from the right hand side of the estimating equation. It shows a series of horse-race regressions, including additional independent variables as listed in the "specification" legend at the bottom of the table, to assess the relative importance of peer parent beliefs and other determinants of peer effects.

Table A.7: Analog to Table 8 - horse race regressions using the girl peers' parents' beliefs measure

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A outcome: Believes boys are better than girls at learning math						
Peer parent beliefs (PPB)	0.017	0.015	0.013	0.012	0.011	0.011
	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)
PPB x female	0.025*	0.028**	0.031**	0.033**	0.032**	0.033***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
R-squared	0.166	0.168	0.168	0.168	0.169	0.170
Number of observations	8,056	8,056	8,056	8,056	8,056	8,056
Panel B outcome: Midterm math test score						
Peer parent beliefs (PPB)	-0.054	-0.061	-0.056	-0.058	-0.058	-0.057
	(0.037)	(0.037)	(0.038)	(0.038)	(0.037)	(0.036)
PPB x female	-0.023	-0.014	-0.016	-0.014	-0.015	-0.014
	(0.025)	(0.025)	(0.025)	(0.026)	(0.026)	(0.025)
R-squared	0.194	0.198	0.199	0.199	0.199	0.200
Number of observations	8,027	8,027	8,027	8,027	8,027	8,027
Specification						
Baseline controls	X	X	X	X	X	X
Peers' parents' education		X	X	X	X	X
Peers' parents' income			X	X	X	X
Peers' parents' hukou status				X	X	X
Proportion of peers female					X	X
Peers' cognitive ability scores						X

Note: this table is the analog to Table 8, but using the index for girl peers' parent beliefs instead of that for all peers' parents. It shows a series of horse-race regressions, including additional independent variables as listed in the "specification" legend at the bottom of the table, to assess the relative importance of peer parent beliefs and other determinants of peer effects.

Table A.8: Analog to Table 8 - horse race regressions using the girl peers' parents' beliefs measure and removing own parent beliefs

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A outcome: Believes boys are better than girls at learning math						
Peer parent beliefs (PPB)	-0.006	-0.007	-0.010	-0.012	-0.012	-0.012
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)
PPB x female	0.036***	0.038***	0.039***	0.040***	0.040***	0.040***
	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.015)
R-squared	0.084	0.086	0.087	0.087	0.088	0.090
Number of observations						
Panel B outcome: Midterm math test score						
Peer parent beliefs (PPB)	-0.042	-0.049	-0.044	-0.046	-0.046	-0.045
	(0.037)	(0.037)	(0.038)	(0.038)	(0.037)	(0.036)
PPB x female	-0.034	-0.024	-0.026	-0.024	-0.025	-0.024
	(0.025)	(0.026)	(0.026)	(0.027)	(0.027)	(0.026)
R-squared	0.188	0.193	0.193	0.193	0.193	0.194
Number of observations						
Specification						
Baseline controls	X	X	X	X	X	X
Peers' parents' education		X	X	X	X	X
Peers' parents' income			X	X	X	X
Peers' parents' hukou status				X	X	X
Proportion of peers female					X	X
Peers' cognitive ability scores						X

Note: this table is the analog to Table 8, but using the index for girl peers' parents' beliefs instead of that for all peers' parents, and excluding the own parent beliefs variable and its interaction with student gender from the right hand side of the estimating equation. It shows a series of horse-race regressions, including additional independent variables as listed in the "specification" legend at the bottom of the table, to assess the relative importance of peer parent beliefs and other determinants of peer effects.

Table A.9: Analog to Table 8 - horse race regressions using the boy peers' parents' beliefs measure

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A outcome: Believes boys are better than girls at learning math						
Peer parent beliefs (PPB)	0.043***	0.040***	0.040***	0.039***	0.037***	0.034***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
PPB x female	-0.015	-0.012	-0.012	-0.012	-0.011	-0.005
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
R-squared	0.166	0.168	0.168	0.168	0.169	0.170
Number of observations	8,057	8,057	8,057	8,057	8,057	8,057
Panel B outcome: Midterm math test score						
Peer parent beliefs (PPB)	0.081**	0.066*	0.069**	0.069**	0.067*	0.062*
	(0.037)	(0.035)	(0.034)	(0.035)	(0.034)	(0.033)
PPB x female	-0.045*	-0.042*	-0.040*	-0.041*	-0.039*	-0.033
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)
R-squared	0.194	0.198	0.198	0.199	0.199	0.199
Number of observations	8,028	8,028	8,028	8,028	8,028	8,028
Specification						
Baseline controls	X	X	X	X	X	X
Peers' parents' education		X	X	X	X	X
Peers' parents' income			X	X	X	X
Peers' parents' hukou status				X	X	X
Proportion of peers female					X	X
Peers' cognitive ability scores						X

Note: this table is the analog to Table 8, but using the index for boy peers' parents' beliefs instead of that for all peers' parents. It shows a series of horse-race regressions, including additional independent variables as listed in the "specification" legend at the bottom of the table, to assess the relative importance of peer parent beliefs and other determinants of peer effects.

Table A.10: Analog to Table 8 - horse race regressions, using the boy peers' parents' beliefs measure and removing own parent beliefs

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A outcome: Believes boys are better than girls at learning math						
Peer parent beliefs (PPB)	0.033**	0.029**	0.028**	0.026*	0.025*	0.020
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
PPB x female	-0.022	-0.018	-0.019	-0.019	-0.018	-0.010
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
R-squared	0.084	0.086	0.086	0.086	0.087	0.089
Number of observations						
Panel B outcome: Midterm math test score						
Peer parent beliefs (PPB)	0.076**	0.061*	0.064*	0.063*	0.061*	0.056*
	(0.037)	(0.035)	(0.034)	(0.034)	(0.034)	(0.032)
PPB x female	-0.057***	-0.053**	-0.052**	-0.052**	-0.051**	-0.044*
	(0.024)	(0.023)	(0.023)	(0.024)	(0.024)	(0.025)
R-squared	0.188	0.192	0.193	0.193	0.193	0.194
Number of observations						
Specification						
Baseline controls	X	X	X	X	X	X
Peers' parents' education		X	X	X	X	X
Peers' parents' income			X	X	X	X
Peers' parents' hukou status				X	X	X
Proportion of peers female					X	X
Peers' cognitive ability scores						X

Note: this table is the analog to Table 8, but using the index for boy peers' parents' beliefs instead of that for all peers' parents, and excluding the own parent beliefs variable and its interaction with student gender from the right hand side of the estimating equation. It shows a series of horse-race regressions, including additional independent variables as listed in the "specification" legend at the bottom of the table, to assess the relative importance of peer parent beliefs and other determinants of peer effects.

Table A.11: Analog to Table 9 - effects by duration of exposure after removing own parent beliefs

	Believes boys are better than girls at learning math		*Perceived difficulty of current math class*		*Midterm math test score*	
	(1)	(2)	(3)	(4)	(5)	(6)
	Grade 7	Grade 9	Grade 7	Grade 9	Grade 7	Grade 9
Peer parent beliefs (PPB)	0.004	0.028	0.004	-0.030**	0.039	0.086*
	(0.028)	(0.018)	(0.023)	(0.014)	(0.068)	(0.045)
PPB x female	-0.020	0.017	0.018	0.038***	-0.048	-0.123***
	(0.020)	(0.018)	(0.012)	(0.013)	(0.032)	(0.046)
Female	-0.163***	-0.083*	0.010	0.129***	0.315***	0.078
	(0.038)	(0.048)	(0.033)	(0.033)	(0.061)	(0.093)
Mean in sample	0.504	0.572	0.546	0.619	-	-
Observations	5,571	2,794	5,706	2,829	5,585	2,749

Note: this table is the analog to Table 9 but excluding the own parent beliefs variable and its interaction with student gender from the right hand side of the estimating equation. It presents results for the effect of exposure to peers whose parents believe $B_m > G_m$ on children's beliefs and performance, estimated separately for those in grade seven and those in grade nine. Those in grade nine have been exposed to their peers for two years longer than those in grade seven. The dependent variable in Columns 1-2 are coded as 0 = No, 1 = Yes. In Columns 3-4, the dependent variable is coded as 0 for low perceived difficulty and 1 for high perceived difficulty. In Columns 5 and 6, the dependent variable is continuous with SD = 1. We omit the aspirations results for simplicity. They are uniformly not statistically significant.

Table A.12: Analogue to Table 9 - effects by duration of exposure, only schools with grade 9

	Believes boys are better than girls at learning math		*Perceived difficulty of current math class*		*Midterm math test score*	
	(1)	(2)	(3)	(4)	(5)	(6)
	Grade 7	Grade 9	Grade 7	Grade 9	Grade 7	Grade 9
Peer parent beliefs (PPB)	0.030	0.034**	0.006	-0.028	-0.089	0.046
	(0.032)	(0.017)	(0.034)	(0.020)	(0.065)	(0.032)
PPB x female	0.021	0.025	0.035	0.029**	-0.030	-0.089***
	(0.022)	(0.020)	(0.024)	(0.015)	(0.050)	(0.030)
Own parent beliefs (OPB)	0.285***	0.299***	-0.051**	-0.076***	0.165***	0.135***
	(0.027)	(0.028)	(0.026)	(0.029)	(0.039)	(0.050)
OPB x female	0.012	0.032	0.130***	0.187***	-0.307***	-0.291***
	(0.033)	(0.033)	(0.040)	(0.040)	(0.067)	(0.064)
Female	0.116	0.293**	-0.110	0.155	0.946***	1.087***
	(0.259)	(0.141)	(0.146)	(0.128)	(0.384)	(0.365)
Mean in sample	0.521	0.571	0.533	0.617	-	-
Observations	2,849	2,643	2,915	2,674	2,846	2,600

Note: this table presents results for the effect of exposure to peers whose parents believe $B_m > G_m$ on children's beliefs and performance, estimated separately for those in grade seven and those in grade nine, and restricting our sample to only schools that maintain the random assignment introduced in grade 7 through to grade 9. The dependent variable in Columns 1-2 are coded as 0 = No, 1 = Yes. In Columns 3-4, the dependent variable is coded as 0 for low perceived difficulty and 1 for high perceived difficulty. In Columns 5 and 6, the dependent variable is continuous with SD = 1. In Table A.11, we show the analog to these results generated without own parent beliefs on the right hand side. We omit the aspirations results for simplicity. They are uniformly not statistically significant.

Table A.13: The impact of exposure to peers whose parents believe $B_m > G_m$ on Chinese and English test scores

	(1) Midterm Chinese test score	(2) Midterm English test score
Peer parent beliefs (PPB)	0.068	0.046
	(0.044)	(0.048)
PPB x female	-0.042	-0.037
	(0.027)	(0.026)
Own parent beliefs (OPB)	0.024	0.054*
	(0.034)	(0.029)
OPB x female	-0.021	-0.054
	(0.045)	(0.040)
Female	0.549***	0.438***
	(0.085)	(0.090)
Observations	7,713	7,713

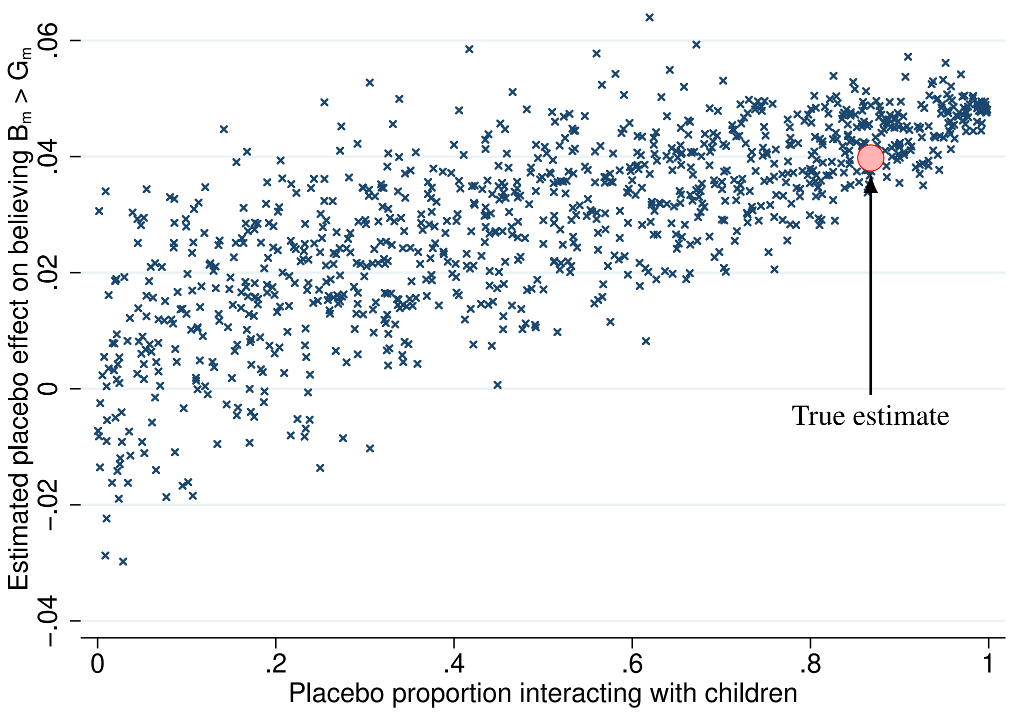
Note: this table shows an analog to Column 1 of Table 6 for performance on standardized (mean = 0, SD = 1) Chinese and English midterm test scores. Note that we have slightly more missing scores for these tests than for mathematics.

Appendix: interaction between peer parents and children

We would like to measure the extent to which belief transmission from peer parents travels from the peer parent to the peer, and then to the child, as opposed to directly from the peers' parents to the child. Our best proxy for this is to use the variable which records each parent's response to the question of whether or not they know at least some of their child's friends. We interact this with the peer parent beliefs test, generating an alternative measure of peer parent beliefs: a measure of the proportion of parents who report knowing their child's friends *and* who believe $B_m > G_m$. We call this "PPB_{int}." We then substitute PPB_{int} for our normal peer parent beliefs measure in equation 1, and estimate the effect of exposure to *this* type of peer on whether or not the child herself believes that boys are better than girls at learning math. This generates an estimate of β_1 of 0.41, slightly smaller than the 0.46 we get with the un-interacted measure of peer parent beliefs in Table 4.

To simulate how our estimate of β_1 for PPB_{int} varies with the proportion of parents included in the measure, as opposed to the proportion who actually interact with their children's friends, we run another simulation. We generate 1,000 draws of a random variable, uniformly distributed between 0 and 1, for the "placebo" proportion of parents who interact with their children's friends. For each draw, we then generate a new random variable for each child's parent with the same potential values (0/1) as the interaction and the same expected value as that draw's overall placebo proportion of parents who interact with their children's friends. We use this to generate a new, placebo PPB_{int} variable for each child within their classroom. We use this to then generate an estimate of β_1 for each of these 1,000 placebo versions of PPB_{int}. We plot these in Figure A.3, overlaying onto the plot the original estimate of β_1 for the true PPB_{int} variable. This plot shows a monotonic increase in effect size as the proportion increases. Furthermore, the estimate of β_1 for the true PPB_{int} variable falls well within the range of estimates for placebo interaction levels similar to the true interaction level. This suggests that the true variable has no more descriptive power than a random sample of an equal proportion of parents (who may or may not interact with their children's friends).

Figure A.3: Simulation: placebo interaction between parents and kids and belief transmission



Note: this figure shows the 1,000 estimates of β_1 generated using 1,000 draws of placebo PPB_{int} variables, i.e., interacting the peer parent beliefs variable with a random variable (possible values 0/1) with expected value of each draw (itself sampled randomly from the uniform distribution over [0,1] for each draw) shown on the x-axis.